Appropriate Entrepreneurship?
The Rise of China and the Developing World

Josh Lerner
Junxi Liu
Jacob Moscona
David Y. Yang*

February 23, 2024

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 growth 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, entrepreneurship increased substantially in other emerging markets, particularly in sectors dominated by Chinese companies. 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. 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 positive consequences, including a rise in serial entrepreneurship, cross-sector spillovers, innovation, and broader measures of socioeconomic well-being. Together, our findings suggest that developing countries benefited from more "appropriate" businesses and technology pioneered by China, and that a system where only rich countries lead in innovation could limit entrepreneurial activity in large parts of the world.

*Lerner: Harvard University and NBER. Email: jlerner@hbs.edu. Liu: University of Warwick. Email: junxi.liu@warwick.ac.uk. Moscona: Harvard University. Email: moscona@fas.harvard.edu. Yang: Harvard University, BREAD, CIFAR, and NBER. Email: davidyang@fas.harvard.edu. Jen Beauregard, Billy Chan, Kevin Chen, Peter Donets, Shai-Li Ron, Kathleen Ryan, Chris Scazzero, and Roger Zhang provided excellent research assistance. Peter Escher, Ted Chan, and Dan Cook were helpful in answering many questions about PitchBook data and methodology. Several practitioners, including Ruzgar Barisik, Peter Cornelius, Teddy Himler, Martell Hardenberg, Jeff Schlapinski, and Andrea Viski were generous in sharing their perspectives on data and analytic questions. We thank Harvard Business School's Division of Research and the Harvard Department of Economics for research support. Helpful comments were provided by participants at seminars and conferences at College de France, Columbia University, the Council on Foreign Relations, Duke University, the FOM Research Group, Harvard University, Tsinghua University, and the Universities of Hong Kong and Toronto, as well as the 2023 AIEA/NBER conference and the Fall 2023 NBER BREAD conference. Lerner has received compensation for advising limited partners in venture funds, venture capital groups, and governments designing policies relevant to venture capital. All errors and omissions are our own.

1 Introduction

Global investment in innovation and entrepreneurship has traditionally been concentrated in a small set of high-income countries. Slow or absent technology diffusion to the rest of the world is a dominant explanation for vast global differences in income and productivity (Keller, 2004). How does the rise of an emerging economy as a new center of global innovation affect international technology transfer?

A first perspective suggests that the global 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 primary obstacle to development. Technology "leapfrogging" to the frontier 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 technologies that are suited to the rich countries that develop them but often "inappropriate" elsewhere. For example, innovators may prioritize capital- or skill-intensive technologies that are less productive where capital and skilled labor are scarce. Frontier technologies can remain inappropriate in large parts of the world even in the long run to the extent that they target characteristics — like culture, geography, or taste — that differ persistently across countries.[2] According to this perspective, the rise of a new center of innovation may have major consequences by shifting the global focus of innovation and developing technologies that are suited to a different set of contexts.

We study this question by investigating the international ramifications of China's emergence as a global hub for innovation and entrepreneurship. We focus on high-growth entrepreneurship and venture capital (VC) investment, which 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

[1] Parente and Prescott (1994, 2002) argue that local barriers to technology adoption prevent convergence across countries, while Barro and Sala-i Martin (1997) use a neoclassical framework to show how the diffusion of ideas from the frontier can lead to long-run convergence. Lee and Lim (2001) and Tonby et al. (2020) argue that technological leapfrogging — adopting frontier technology without passing through intermediate steps — could be an important driver of future development.

[2] Inappropriateness driven by skill and capital differences is described by Basu and Weil (1998) and Acemoglu and Zilibotti (2001). For work on inappropriateness driven by persistent differences across countries, see Moscona and Sastry (2023) on how innovation in agriculture is designed for the ecological conditions of high-income countries, as well as Kremer (2002) and Kremer and Glennerster (2004) on how biomedical research ignores diseases that predominately affect low-income countries.

[3] See, among others, Kortum and Lerner (2000), Samila and Sorenson (2011), Puri and Zarutskie (2012),

last decade has witnessed a dramatic rise in China, unparalleled by any other country. In 2001, the US represented the location of 88% of global venture dollars invested, and other developed countries the majority of the remainder (7%). By 2019, China had surged to account for 38% of the global total while the US accounted for 42%, even though the level of investment in the US increased throughout the period.

A range of qualitative evidence suggests that the rise of China as a counterpoint to the US may have reshaped the diffusion of entrepreneurship in developing countries. A key characteristic of the selection of new ventures by financiers is their reliance on parallels to earlier, successful businesses. Traditionally, highly successful US firms have served as the template after which firms elsewhere have stylized themselves.[4] But businesses that are suitable for the US may not be right elsewhere, and those that would have flourished elsewhere may not be suitable in the US. This misalignment could be particularly severe in low-income regions. Anecdotally, as China has taken off, Chinese firms have focused on solving different problems than US firms and have been increasingly emulated by emerging-market startups around the globe. For example, while companies geared toward online elementary education never took off in the US, perhaps because of better access to brick-and-mortar education, there was a dramatic increase in Chinese entrepreneurial activity in the 2010s, followed by an emerging market boom, most notably in India. Local investors in these startups consciously emulated Chinese business models: Akhil Shahani, the Managing Director of the India's Shahani Group, noted, "[I]t would be safe to say that the traits of the Chinese economy which helped its EdTech industry boom find their parallels in India, which indicates a very bright future for Indian EdTech."[5]

In this paper, we focus on three specific questions. First, did the rise of VC in China increase entrepreneurship in *other* emerging markets? If so, was this driven by the fact that businesses developed in China were more suited to the characteristics of those countries, as suggested by the appropriate technology perspective? And finally, were there broader economic benefits of this business and technology diffusion? Affirmative answers to these questions imply that the rise of China shifted the global focus of innovation toward technologies that are more "appropriate" for new parts of the world, which, in turn, benefited from their development. However, as noted above, there are several reasons why the answers to some or all of these questions could be "no." Chinese technology may

Bernstein et al. (2016), and Akcigit et al. (2022).

[4] This approach can be understood as a natural response to the uncertainty and informational asymmetries that surround early-stage companies (Gompers and Lerner, 1999) and is particularly true where the rule of law and contract enforcement are less well established (e.g. Lerner and Schoar, 2005).

[5] Source: `https://inc42.com/features/the-past-present-and-future-of-edtech-startups/`. In Section 2.2, we describe additional examples of this pattern.

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 second order.[6] Thus, in order to determine the global consequences of a new nation leading global entrepreneurship, it is essential to turn to empirical analysis.

To answer these questions, we combine several data sources and new empirical measures. 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. The database includes a description of each company, as well as information about each financing round — including the size and capital providers.[7] In total, we compile data on 169,505 venture deals involving 88,267 firms in 152 countries. This serves as our main source of data and sample for analysis.

Second, in order to examine the impact of China's emergence on venture investment across sectors, we use deep learning neural network tools to categorize firms into 266 sectors, using PitchBook's 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, consistent with the the rise of China shifting 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. In our empirical analysis, we define sectors with above-median Chinese participation (relative to the US) as "China-led" sectors.

Third, we measure the potential "suitability" of Chinese entrepreneurship in each country-sector pair. 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 link each of these variables to one or more of the macro-sectors in the PitchBook data (e.g., indicators related to educational attainment are linked to the EdTech macro-sector); and we 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 the potential appropriateness of Chinese businesses that varies at the country-sector pair level. On average, the measure is higher in developing countries than in developed countries, while an analogous measure of similarity to the US

[6]See, among others, Parente and Prescott (2002) and Parente and Prescott (1994). More specific to the studied context, China's economy may be sufficiently different from other emerging economies, or beholden to political pressures, that businesses developed there are not broadly relevant beyond its borders.

[7]PitchBook has become the industry gold standard for the analysis of venture transactions, especially for international comparisons. Data are gathered through firm/fund contacts, news stories, and regulatory filings. We describe the data in detail and conduct our own validation exercises in Section 3.

is higher in developed countries. However, there is also substantial variation in similarity to China across sectors in each country, which we exploit in our empirical analysis.

We present three sets of findings. First, as the Chinese venture industry rose in importance, emerging market entrepreneurship grew substantially in the sectors dominated by China, while entrepreneurship in developed countries remained on similar trends.[8] This is a first indication that the rise of China spurred new venture activity specific to developing countries. We then move to the core empirical strategy where, instead of comparing developed to developing countries, we compare country-sector pairs where Chinese technology is likely to be more or less appropriate. We document that the global growth in entrepreneurship in sectors led by China is driven by country-sector pairs where *ex ante* economic and social data indicate that Chinese technology would be most suitable. Even within emerging markets, the effect of the rise of China on entrepreneurial activity is entirely driven by country-sector pairs with high measured suitability. This effect is driven largely by *local* investors, rather than investors from China or the US.[9] To support a causal interpretation of the main result, we report a series of falsification tests as well as a set of estimates that exploit early and largely idiosyncratic Chinese startup successes as predictors of Chinese sector-level growth.

Our baseline estimate suggests that a one standard deviation increase in measured socioeconomic suitability is associated with a 214% increase in venture investment deals among China-led sectors in the post period. Aggregating these estimates across all country-sector pairs, we find that the rise of China increased emerging market venture activity outside of China by 42%. If anything, the estimates are larger if we focus on high-value deals or larger investment sectors.

Turning to dynamics, we do *not* observe that sector-by-country economic similarity to China predicts venture activity *prior* to the rise of China's venture industry. Instead, and consistent with qualitative accounts, early in our sample period 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.

Second, after presenting the baseline estimates, we investigate the mechanisms that

[8]This "triple-difference" specification includes all two-way fixed effects, making it possible to fully absorb any country-level trends (country-by-year effects), global sector-level trends (sector-by-year effects), or any average differences in the direction of VC investment across countries (country-by-sector effects).

[9]A one standard deviation increase in suitability leads to a 116% increase in local investment. The effects on Chinese and US investments are about a quarter the size and neither is statistically 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.

drive the main results. Using Natural Language Processing (NLP) tools to measure similarity in business description across company pairs, we show that the growth in entrepreneurship following China's rise is 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. These findings suggest that entrepreneurs in these countries were not only working in sectors dominated by China, but were also actively following the business ideas of their Chinese counterparts. We then show that the main results are driven both by an increase in the number of very young firms and an increase in investment in existing firms. Thus, the rise of Chinese VC 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 the results are driven by explicit political factors. Political links between China and other countries, measured either using their similarity in UN voting patterns of regime characteristics, do not seem to drive our baseline results. The results are also similar after excluding from the analysis sectors that are included by the Chinese government in published lists of strategic sectors. In fact, the results are substantially weaker after restricting attention to the strategic sectors, perhaps indicating that investment growth driven by political considerations had weaker international spillover effects.

Third, we study the broader economic consequences of this rise in VC investment in developing countries. We first focus on firm-level effects and, using data on company outcomes, find large positive effects on companies that are acquired or go public, as well as firms that have not yet exited, 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 find that these serial entrepreneurs start subsequent companies in sectors that are *not* led by China. That is, the initial growth in entrepreneurship following the rise of China had positive cross-sector spillover effects by generating a pool of serial entrepreneurs who branched out from the China-led sectors in which they started.

This growth in entrepreneurship was also associated with a rise in broader forms of innovative activity and economic development. 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 established locally 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, indicating that city-level effects extended beyond the transmission of business ideas directly from China.

These cities also experienced a substantial increase in patenting activity, suggesting that the rise of local entrepreneurship had broader positive effects on local innovation. These patterns are especially strong for cities in developing countries, consistent with all previous evidence that the rise of China disproportionately boosted local entrepreneurial ecosystems in emerging economies. 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 measure of well-being constructed from the World Bank development indicators associated with the corresponding sector.

Taken together, our results indicate that the historic concentration of investment in entrepreneurial innovation based in the US has limited VC growth in developing countries. The rise of China led to a shift in the types of businesses that were developed 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 and global productivity impacts. We discuss these more speculative consequences of our findings in the conclusion.

This work builds on three strands of existing literature. First, there is a large body of work on international technology diffusion (see, e.g., Barro and Sala-i Martin, 1997; Eaton and Kortum, 2002; Keller, 2002, 2004; Comin and Hobijn, 2010; Comin and Mestieri, 2014, 2018; Giorcelli, 2019). Particularly relevant is a subset of this work focusing on how the "appropriateness" of technology shapes the distribution of output across countries (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006; Moscona and Sastry, 2023). Existing work in this area has highlighted the current lack of appropriate technology for developing countries, and the key potential solution to this problem is a shift in the direction of innovation toward technologies that benefit low-income regions. We identify the consequences of such a shift, driven by the rise of a large, new innovation hub, and show how it alters the global diffusion of business ideas and technology.

We also extend existing ideas about technology diffusion to the study of entrepreneurship. The local focus of Chinese entrepreneurship underlying our results builds on existing work documenting "home bias" in technology development (Costinot et al., 2019; Moscona and Sastry, 2023). Moreover, much of the technology diffusion literature says relatively little about the mechanisms that drive diffusion. Inasmuch as the literature has investigated mechanisms, it has focused on the role of governments (Giorcelli, 2019), academia (Aghion et al., 2023), or worker mobility and shared supply chains (Bai et al., 2022). Financiers are a neglected but potentially important channel for diffusion.[10]

A second strand of related literature is the growing body of work on innovation in China (e.g. Holmes et al., 2015; Aghion et al., 2015; Fang et al., 2017; Wei et al., 2017; Chen et al., 2021; König et al., 2022; Beraja et al., 2023b). We investigate the international consequences of Chinese innovation in recent decades and document that it has affected patterns of entrepreneurial activity around the world.

Finally, we build on the small existing body of work on venture capital in emerging economies, such as Lerner and Schoar (2005) and Colonnelli et al. (2023). 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 developing countries.

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. 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). 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 rapidly changed since then: between 2014 and 2021, China captured an average of 22.01% of global venture dollars, amounting to US$ 63.04 billion in average annual investment. These totals repre-

[10] More generally, very little has focused on knowledge flows from startups. One exception is Akcigit et al. (2024), which focuses on knowledge flows to corporate investors in US startups.

sented a 501% and 2,060% increase compared to the 2013 share and level.[11] The take-off of the Chinese venture sector had numerous drivers: these included 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 policy (such as the creation of robust public markets where venture-backed could go public).

Many examples indicate that these Chinese ventures represented true innovative accomplishments, and not just copies of business models developed elsewhere. Many of the China-led sectors seem to feature "recombinant innovations," to use the terminology of Weitzman (1998) (who traces the concept back to Poincaré and Schumpeter): i.e., the reconfiguration and combination of existing ideas. For instance, social commerce firms combined well-known tools such as e-commerce and social networks to create a setting where potential customers interacted to facilitate the online buying and selling of products and services. Many of these recombinant innovations (e.g., in FinTech) were only possible due to the scale of and (historical) freedom offered to major Chinese technology platforms (e.g., Alibaba, Tencent). In other cases, such as unmanned aerial vehicles, manufacturing innovations such as the ability to frequently update products (allowing the aggressive incorporation of the latest technologies), exacting quality control, and deep integration with key suppliers like camera makers led to the creation of products similar in quality to those built elsewhere but with dramatically lower prices. In yet other areas, Chinese firms appear to have achieved clear technological superiority, such as the manufacture of electric vehicle batteries.

The size of China's venture industry is unprecedented and unique among developing countries. 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. The comparison is presented in Appendix Table A.1. China constituted 13.44% of the world's venture investment when it reached US$ 12,244 GDP per capita. In contrast, none of the other emerging or recently developed countries represented more than 1% of the global venture investment when they reached this level of income. A sim-

[11] The recent rise of Chinese venture investment and entrepreneurship reflects, in part, a broader rise in Chinese innovation. Appendix Figure A.1 illustrates China's growing share of global R&D investment and global scientific publications. While the share of innovation happening in China has increased using both measures, the pattern is less extreme and sudden than is the case for VC investment. One reason that we focus on VC investment in this paper is because of the particularly rapid and dramatic shift in Chinese investment, making it possible to empirically identify the consequences of China's rise.

ilar 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. Appendix Figure A.2 traces the countries' growth in terms of GDP per capita alongside their venture investment. While the amount of venture investment rises as countries develop throughout the world, the upward sloping curve is substantially shifted to the left for China.[12]

2.2 Industry benchmarks and diffusion from China

A range of examples suggest that the rise of venture capital in China could affect entrepreneurial activity in other emerging markets because Chinese companies are learning to solve problems and meet consumer demands that are common there. 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. The results in Section 5 are consistent with this pattern, suggesting that a majority of the growth in emerging market venture activity is driven by local investors.

Our empirical approach is grounded in the observation that venture investors frequently look for indications that new ventures correspond in important ways to ones that have proven successful in the past. This is, in part, because venture capitalists invest in settings 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. In emerging markets, many firms have sought to emulate successful concepts from other countries, such as e-commerce, mobile payments, and buy now/pay later.[13]

While many of the early efforts to replicate highly successful ventures focused on US successes, in recent years Chinese firms have been increasingly emulated. Returning to the example of startups geared toward elementary and secondary education that we dis-

[12]It is interesting to note that while India's GDP per capita is still less than half of that in China, it captured more than 5% of the world's venture investment in 2020 and 2021. This could be, in part, a consequence of the model set by China and the applicability of Chinese business models in India, as our findings suggest. The rise of India could also have independent consequences for entrepreneurship in developing countries, which would be interesting to explore in future work.

[13]For instance, in ride-sharing sector, there are many dozens of companies in emerging economies, including Cacao Chuxing (founded in China), Careem (UAE), Didi (China), Easy Taxi (Brazil), Gett (Israel), Okada (Nigeria), Grab (Malaysia), 99 (Brazil), Ola (India), Patha (India), QuickRide (India), SWAT Mobility (Singapore), T3 Mobile (China), Wicked Ride (India), and Zipp (India). In some cases, these businesses are adapted to the local market; in others, business models from elsewhere are largely cloned.

cuss in the introduction, Appendix Figure A.3a plots the timing and amount of venture investment received by startups in this sector around the world. There are three distinct periods of venture investment. Prior to 2017, there was little initial funding for any companies in this sector, including the ones based in the US. As a result, there does not exist a US benchmark for the elementary and secondary education startup sector that could be emulated in emerging markets. Between 2017 and 2021, there was dramatic growth of Chinese investment, followed shortly thereafter by investment in other developing countries. Appendix Figure A.3b plots the size and date of funding rounds for several important companies in the sector. Yuanfudao and Zuoyebang, two sector leaders in China, received a total of 11 rounds of investments amounting to US$ 7.27 billion during this period. Since 2020, following the rise of the two Chinese startups, Byju in India saw a dramatic rise in fundraising, gathering over US$1 billion in 2021 alone.

There are several similar examples beyond the education technology sector. One is social commerce — the method of selling products and services to consumers directly on social media platforms, often with features such as group buying and user-curated content — which has found particularly high demand in areas where food spending (as a share of income) is high and where last-mile food delivery logistics are complex.[14] Social commerce platforms were originated in China, before taking off in other developing countries around the world. The founder of Brazil's Favo, for example, says that "[w]hen he learned about social commerce from a friend, he traveled to China in 2019 to see it firsthand. [He] came back [to Brazil] and knew this was what [he] wanted to build."[15] Another case is last-mile delivery; the formation of the Indonesian delivery unicorn, J&T Express, for example, was motivated by the experience of its co-founder while serving as a country manager for a major Chinese electronics firm that navigated similar issues.[16]

Writing by practitioners suggests that these examples represent a broader phenomenon. Christopher Schroeder, an investor focused on the Middle East, summarizes this pattern: "For all the obvious cultural and geographic differences, [companies in China] have navigated challenges not contemplated in the West—navigating particularly hard last mile logistics, dealing with rapidly changing regulatory regimes, educating millions of con-

[14]The following report describes the rise in social commerce platforms more broadly: https://www.sturgeoncapital.com/wp-content/uploads/2022/07/Sturgeon-Insights-Social-Commerce.pdf

[15]For the quote, see here: https://techcrunch.com/2021/10/06/tiger-global-backs-favo-which-is-building-an-easier-way-for-latin-americans-to-order-groceries-online/. For another example in Kenya: https://techtrendske.co.ke/2022/03/31/kenyan-social-commerce-platform-tushop-raises-3m-in-pre-seed-funding/.

[16]Source: https://asia.nikkei.com/Business/36Kr-KrASIA/Boom-or-bust-The-story-of-J-T-Express-in-China and https://www.forbes.com/sites/ywang/2023/06/20/chinese-logistics-entrepreneur-becomes-a-billionaire-as-his-jt-express-gears-up-for-hong-kong-ipo/?sh=3a81b24951cc

sumers to use FinTech who never had a bank account among others. It should come as no surprise that massively successful companies in China are often models for how it is done to the rest of the world as much as Silicon Valley."[17]

2.3 Venture capital in emerging markets

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 emerging market 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. These firms are likely to be a key source of economic dynamism (Haltiwanger et al., 2013; Ayyagari et al., 2017). We focus on companies that went public between 2003 and 2022, given the lower data quality in earlier years and the fact that these years largely align with the sample period in our main analysis. 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 the market capitalization and (strikingly) almost 50% of the R&D spending of such firms. Venture investments have become a non-trivial component of firm growth in emerging markets and an even larger share of R&D.

How significant is the share of innovation by venture-backed firms in these countries more generally? To investigate this, we examine US patents awarded between 2013 and 2022 to all institutional (non-individual) assignees based in developing nations outside of China.[18] We use the same definition of emerging markets outside of China as in Figure 1, with the exception of deleting patent awards to assignees based in the Cayman Islands and Korea (see Appendix A for more details). We find that venture-backed firms represent 31.32% of all such 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. (2023), the weighted share rises to 41.66%. Thus,

[17] For the original quote, see here: `https://christophermschroeder.substack.com/p/chinas-evolving-global-tech-expansion?utm_source=post-email-title&publication_id=28991&post_id=137487377&utm_campaign=email-post-title&isFreemail=true&r=7tj8a&utm_medium=email`.

[18] 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.

venture-backed companies represent a substantial share of overall innovation in low and middle income countries.

3 Data and measurement

3.1 Venture deals around the world

The primary data source for this paper's analyses of global venture deals is PitchBook, which is one of the major databases of venture capital investment.[19] From its founding in 2007, it was designed to have a world-wide focus. It has been used for international comparisons by the National Venture Capital Association, US National Science Board, and others. The information in the PitchBook database is gathered from contacts with funds and portfolio firms, news stories, and regulatory filings.

We compile comprehensive venture investment deals around the world between 2000 and 2019.[20] In particular, we extract from the database the dates, size, and participants in each financing round between 2000 and 2019, as well as short (averaging 44 words) descriptions of each company, company location, company founders, company outcome as of mid-2022 (e.g., went public, acquired, bankruptcy), and other information. We focus on deals categorized by PitchBook as "Early-Stage VC" or "Later-Stage VC" and drop failed or canceled deals.[21]

In Table 1, Panel A, we present a series of summary statistics. The compiled data covers 88,267 companies from 152 countries that received 169,505 venture deals in total for the period of 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.

One potential concern is with the quality of these data. Kaplan and Lerner (2017) highlight some of the inconsistencies between commercial venture databases, such as disparities introduced by various data sourcing approaches and varying definitions of what

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

[20]While coverage before 2000 is spotty, PitchBook made considerable efforts to backfill earlier years in the 2000s. We end our main analysis in 2019 in order to make sure that none of our findings are driven by changes in investment patterns due to COVID-19. However, we show that our findings are robust (and if anything, larger in magnitude) when we include 2020 and 2021 in the sample (see Table A.5).

[21]We validated that the (excluded) growth equity category does not have significant numbers of later-stage VC deals.

constitute a venture capital transaction.[22] To validate the PitchBook data, we compare our measure of reported Chinese venture capital activities — where data access and definitional issues are likely to be the most severe (Chen, 2023) — with that reported by two other commercial databases that specialize in Chinese VC: Zero2IPO and China Venture Institute. Reassuringly, we find that the PitchBook coverage on Chinese VC activities lies generally between the other two estimates. Appendix Figure A.4 presents comparisons for the volume of transactions over the sample that take place in China. In Appendix B, we discuss the exercise in greater detail, along with other evidence of validity.

3.2 Categorizing firms into sectors

We use country-level investment in a specific sector as the primary unit of analysis. 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 scheme, which divides firms into a three-level structure consisting of markets, segments, and subsegments. Throughout our analysis, we define sectors as the "subsegments" in the PitchBook structure (most detailed level) and define macro-sectors as the fifteen "markets" in the PitchBook structure (broadest level). Many of the sectoral categories are extremely narrow, such as the *Natural Language Technology* sector in the *AI and ML* macro-sector, the *Crime Surveillance and Fraud Detection* sector in the *FinTech* macro-sector, and the *Remote Patient Monitoring (RPM)* sector in the *Retail Health Tech* macro-sector.

PitchBook's analysts have assigned 26,524 companies by hand to these sectors. We fine-tune Bidirectional Encoder Representations from Transformers (BERT) models for each sector using these human classifications and the paragraph-long text that describes the company's business mission, business model, and area of business as the training set.[23] We then use our fine-tuned models to predict on the universe of firms that PitchBook tracked. As a result, 88,267 companies, or approximately 93.73% of the companies that have venture capital deals tracked by PitchBook, are classified into 266 sectors.[24]

[22]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 some of its 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 the conclusions of a comparison study of venture capital databases by Retterath and Braun (2022), though it focuses on European transactions.

[23]These descriptions are written 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.

[24]We use the full set of PitchBook-assigned data as our training data and assign the universe of companies to sector categories. We fine-tune a binary classification model for each sector and determine independently whether a company belongs to a given sector or not. In total, we are able to assign 402,695 companies, or approximately 91.09% of the companies tracked by PitchBook (whether having VC deals or not). Some

Overall, our baseline categorization is able to achieve a high level of accuracy, precision, and recall: when testing on uncontaminated data sets, the average accuracy across sectors is 0.97, and the average precision and recall are 0.77 and 0.78 among sectors that have at least 100 companies in the training data.

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.

Once we have categorized firms into different sectors, we can define whether global venture investment in a given sector is led by China. There is substantial heterogeneity across sectors in the share of venture deals that take place in China. Importantly, Chinese firms focus on very different areas than US firms, potentially reflecting the very different socioeconomic conditions between them. Figure 2 displays a histogram of Chinese deals in each sector from 2015-2019 as a share of total deals in both China and the US. In some sectors, there are zero or a very small number of deals that take place in China; in other sectors, several of which are described in Section 2.2 and labeled on Figure 2, however, a greater number of deals take place in China compared to the US. In fact, 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 2015-2019 is above the median among all sectors. In addition to the baseline definition, we show that all results are similar (and, if anything, stronger) if 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 2015-2019. 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 relative definition. A smaller but still substantial number (69) are China-led following our stricter definition.[25]

companies are not assigned because they are not predicted to any sector. We merge small sectors (where the number of firms in the human-curated sector is less than 10) with sectors that are closely related to them to increase the categorization precision.

[25]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. The first is the bipolarity of the global venture industry during this period. Outside of the US and China, no single country represented a substantial share of global investment. The second is the large amount of case study evidence,

To illustrate graphically how the rise of China shifted the direction of entrepreneurship across sectors, Figure A.5a plots the (log of the) 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 the rise in Chinese entrepreneurship. Figure A.5b shows directly that, relative to the pre-analysis period, total deals in China-led sectors grew dramatically faster than deals in US-led sectors. 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.

Table 1, Panel B.2, presents summary statistics for the China-led sectors. Emerging markets have more companies and larger deal sizes in China-led sectors than in US-led sectors, whereas countries outside of the emerging markets have more companies and larger deal sizes in US-led sectors. This is a first indication that Chinese VC leadership spills over disproportionately to other emerging markets.

3.3 The suitability 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 similarity to China.

Specifically, 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, the year that we identify as China's "take-off" year in the main analysis. We denote these characteristics as x_c and normalize each characteristic to be in comparable, *z-score* units:

$$\hat{x}_c = \frac{x_c - \mu\left(x_c\right)}{\sigma\left(x_c\right)}.$$

Second, we determine which socioeconomic indicators are most relevant to each of the fifteen macro-sectors in the PitchBook data.[26] For this part of the analysis, we focus on

some of which is described in Section 2, suggesting that the benchmark companies that investors look to when making investment decisions are from the US and China. Thus, the sum of China and the US comprise the relevant set of potential benchmarks. Nevertheless, in Section 4 and Table A.6, we show that all results are very similar if we define China's sector-level leadership based on its share of global deals.

[26]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

these broader sector groupings because it is relatively 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 supply and features of demand that are specific to country-sector pairs — both can shape the appropriateness of Chinese business ideas 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 complementary methods, with different levels of coder freedom.[27] 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 not free to pick-and-choose within each indicator "Topic" category defined by the World Bank; once they deemed one indicator within each Bank-assigned Topic relevant for a particular macro-sector, all indicators with the same topic heading were also assigned. A third method, designed to fully tie the coders' hands, required coders to classify *all* indicators to at least one macro-sector.[28] Reassuringly, our results are very similar across all three coding methods.

Third, we aggregate all characteristics to create a measure of the "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 *suitability* measure, we subtract M_{cs} from its maximum and define this as $ChinaSuitability_{cs}$. The goal of this measure is to capture the potential appropriateness of Chinese technology in each country-sector pair.

The measure captures both variation across countries (it is constructed using country-level indicators) and across macro-sectors within countries (only certain indicators are

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.

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

[28] Appendix Table A.2 gives more examples of the indicators chosen for specific macro-sectors. While the first method allows for the highest amount of freedom (and hence likely greatest precision), the final method allows us to make sure that the results are not driven by which indicators are excluded from or included in the measure.

applied to each macro-sector). Figure 3a displays a map of the country-level variation in $ChinaSuitability_{cs}$. Each country is color-coded based on its average suitability across all fifteen macro-sectors. The set of countries with the highest measured suitability 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 suitability.

We next investigate how this measure of the suitability of Chinese technology differs from an analogously constructed measure of the suitability of US technology. Figure 3b displays a map in which each country is color-coded based on the *difference* between its average China-suitability and its average US-suitability. Blue-colored countries are more similar to the US on average and red-colored countries are more similar to China on average. The countries most similar to the US (compared to China) include Western Europe and other high-income countries (e.g., Australia, Japan). The countries most similar to China (compared to the US) include South and Southeast Asia, as well as large parts of sub-Saharan Africa. While some developing regions have relatively low measures of China-suitability (e.g., sub-Saharan Africa), they are still far more similar to China than they are to the US, suggesting that they might stand to benefit from a shift in technological leadership to one that includes China. On average, non-OECD countries are 0.565 standard deviations more similar to China than they are to the US.

Not only are there large differences in average China-suitability across countries, but there are also large differences across sectors within countries. Appendix Figure A.7 plots the histogram of the maximum difference between sectors in China-suitability for all countries and shows that for most countries, there is a large gap between the most and least suitable sectors. To make this point in greater detail, Figure A.6 displays histograms of China-suitability for AgTech (A.6a) and FinTech (A.6b), after subtracting average suitability across all other sectors in order to zero-in on within-country, cross-sector variation. While Figure 3a showed that India is very similar to China on average, Figure A.6 documents that it has far higher potential suitability in FinTech compared to AgTech. The same is true for Indonesia. Afghanistan, on the other hand, has far higher potential suitability in AgTech compared to FinTech. Canada is also very similar to China in AgTech, highlighting that in certain sectors, high-income countries may also benefit from Chinese technology development.

In our empirical analysis, we exploit this country-by-sector level variation in the potential suitability of Chinese technology. This makes it possible to fully absorb all country-level or sector-level trends, as well as any cross-country differences in specialization.

3.4 Descriptive evidence: emerging markets follow China

Before turning to the main results, we begin by examining the extent to which the rise of China was associated with increased venture activity in emerging markets across the board. This would be a first indication that developing countries around the world might have benefited from the rise of investment in China.

We estimate the following regression specification, separately for emerging and developed economies:

$$y_{cst} = \sum_{\tau} \beta_{\tau} \left(ChinaLed_s * \delta_{\tau} \right) + \alpha_{cs} + \gamma_{ct} + \epsilon_{cst}, \tag{1}$$

where c indexes countries, s indexes sectors, and t indexes years. $ChinaLed_s$ is an indicator that equals one if s has above median Chinese deals, δ_{τ} is an indicator that equals one in year τ, and "emerging economies" are defined as those that were not part of the OECD as of 1980.[29] The outcome of interest, y_{cst}, is the number of deals in the country-sector-year, normalized by the total number of pre-period deals in the country. Two-way fixed effects at the country-sector and country-year level capture all country-level dynamics and differences in specialization across countries. Each β_{τ} captures venture activity in China-led sectors, compared to non-China-led sectors, in year τ.[30]

Panel A of Figure 4 displays estimates of Equation 1, separately for the sample of emerging and developed countries. Estimates of β_{τ} are close to zero during the period before China's rise in both series. However, there is a rapid increase in the estimates for developing countries during the mid-2010s and this increase is entirely absent in developed countries. Panel B reports estimates of the difference between the two series in Panel A and shows that the trends for developing and developed countries sharply and significantly diverge.[31,32]

These results show that the rise of Chinese VC was followed by international growth

[29] These countries are Australia (1971), Austria (1961), Belgium (1961), Canada (1961), Denmark (1961), Finland (1969), France (1961), Germany (1961), Greece (1961), Iceland (1961), Ireland (1961), Italy (1962), Japan (1964), Luxembourg (1961), Netherlands (1961), New Zealand (1973), Norway (1961), Portugal (1961), Spain (1961), Sweden (1961), Switzerland (1961), Turkey (1961), United Kingdom (1961), USA (1961). Source: `https://www.oecd.org/about/document/ratification-oecd-convention.htm`.

[30] Results from a specification with a pooled post period are reported in Appendix Table A.3. Instead of interacting $ChinaLed_s$ or $ChinaLed_s * EM_c$ with year indicators, we instead interact them with an indicator that equals one for all years after 2013. The results tell a very similar story to the dynamic specification.

[31] Since the triple-interaction reported in this figure varies across countries, sectors, and time, the regression specification includes all two-way fixed effects, including sector-time effects that fully absorb any sector-level trends.

[32] Figure A.8 plots VC deal counts in China-led and non-China-led sectors, relative to their corresponding pre-2013 mean, for both developing and developed countries. VC deals rose across all sectors in emerging markets, albeit at a faster pace in China-led sectors. This indicates that the increase in VC investments in China-led sectors did not come at the expense of other sectors (at least in absolute terms).

in the specific sectors that China dominated, but this pattern was restricted to other developing countries. In the next section, we turn to our main empirical analysis where we investigate whether the global diffusion of Chinese technology and business ideas was driven by their potential "appropriateness." We then examine the broader economic consequences of this wave of business and technology diffusion.

4 Main results

4.1 Empirical strategy

Our goal in this section is to investigate whether the global spread of entrepreneurship following the rise of China was driven by the suitability of new businesses and technologies in markets around the world. Our baseline specification estimates differential effects of the rise of China in country-sector pairs whose *ex ante* socioeconomic conditions more closely match those of China. Specifically, we estimate:

$$y_{cst} = \beta\left(ChinaLed_s * Post_t * ChinaSuitability_{cs}\right) + \alpha_{cs} + \gamma_{ct} + \delta_{st} + \epsilon_{cst}, \tag{2}$$

where the *ChinaSuitability* measure, 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.[33] If innovation in high-income countries is productive around the world, or if "leapfrogging" to frontier technology drives technology diffusion, one would expect β=0. One would also expect that β=0 if local barriers to technology adoption are sufficiently high, since then technology would not diffuse regardless of its suitability to the local context. However, if entrepreneurship has an important context-specific component and diffuses disproportionately where it is most "appropriate," one would expect β>0: the rise of China would shift the direction of entrepreneurship and benefit entrepreneurs in contexts that resemble China's socio-economic conditions.

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 China-led sectors. Second, *sector* $*$ *year* fixed effects control for global trends in entrepreneurship for each sector. Finally, *country* $*$ *sector* fixed effects control for differences in entrepreneurial specialization by country.

[33] We defined 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 4.2, 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.

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, but due to unobserved common shock or trend specific to those sectors. For this to bias estimates Equation 2, this shock would also need to be correlated with country-sector socioeconomic similarity to China. To address this possibility directly, Section 4.2.1 presents a series of falsification exercises consistent with a causal interpretation of our estimates, and Section 4.2.2 presents estimates that exploit exogenous variation in sector-specific take-off in China driven by early and idiosyncratic entrepreneurial success.

4.2 Main estimates

Table 2, columns 1-2, present the baseline estimates of Equation 2. The estimates of β are positive and statistically distinguishable from zero ($p < 0.01$). A one standard deviation increase in sector-specific suitability is associated with a 214% increase in venture investments 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 fixed effects. This fully absorbs any differences in trends in the cross-sector distribution of investments between emerging and developing countries. The similar estimate of β, even within emerging markets, also 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* developing countries.[34]

Finally, columns 3-4 of Table 2 return to the effect on all emerging markets by replacing the suitability measure in Equation 2 with an emerging market indicator, but restricts the sample to $country * sector$ sets with low (column 3) vs. high (column 4) values of the suitability measure. The positive effect of China-led growth on emerging market venture investment is strongly driven by country-sector pairs that are more similar to China. The effect is over thirty times larger when focusing on the top three quartiles of the suitability measure compared to the bottom quartile.

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 weighted by

[34]Estimates in Table A.4 further make this point, where we include controls 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 statistically 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 ladder-based mechanism in which technology appropriateness is "vertically" differentiated by development stage (see Atkin et al., 2021, for a recent treatment). In the latter case, we would expect technology to flow from China only to less-developed countries.

deal value (Panel A of Table 3). Thus, the findings are not driven by economically unimportant sectors or small financing rounds. Intuitively, the results are also stronger using the "strict" definition of China-led sectors to construct the independent variable, thereby restricting attention to the sectors in which China's rise in entrepreneurship was most dramatic (Panel B of Table 3).[35]

Together, these findings indicate that venture investments in emerging economies 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.

Sensitivity analyses We conduct a range of additional sensitivity analyses, all reported in the Appendix. First, in Appendix Table A.5, we include the years 2020 and 2021 in the sample (i.e., the COVID years). Second, in Appendix Table A.6 we use 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. The results are all very similar.

Third, in Appendix Table A.7, 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. 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 findings.

Fourth, to show that our main results are not driven by our specific choice of indicators when constructing the suitability measure, we show that the results are very similar using our alternative strategies for assigning indicators to macro sectors (Appendix Tables A.8 and A.9; see Section 3.3 and Appendix C for details).[36] We also address the concern that our findings are driven by a small number of indicators by reproducing our baseline results after reconstructing the suitability measure after one, two, three, or four indicators are randomly excluded from the suitability measure, and repeating each process 500 times. Appendix Figure A.9 shows that this has little impact on our main results.

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

[36]Another decision we had to make when constructing the suitability measure is how we drop indicators or countries in the sample with large amounts of missing data. In our baseline analysis, we exclude countries when greater than 25% of indicator values are missing and exclude indicators when they are missing for greater than 20% of countries. We show in the Appendix that the results are very similar if we use a range of alternative thresholds. These results are reported in Appendix Tables A.10, A.11,A.12, and A.13; they are described in greater detail in Appendix C.

Finally, we show that the results are similar if we identify a separate post-period year for each sector based on the year in which investment surged in China. For each sector and each two-year window, we construct the growth rate in Chinese deals and we define the surge year as the start of the two-year window with the highest growth rate.[37] Appendix Figure A.11 shows the distribution of surge years identified; most sectors are identified to have 2013 as the surge year, which is why we use this year in our baseline analysis.[38] Appendix Table A.14 shows that the results using a sector-specific post period definition are (if anything) slightly larger than our baseline results.

4.2.1 Falsification tests

In this section, we present a series of falsification tests that are all consistent with a causal interpretation of our baseline results. One potential concern with our baseline estimates is that similarity to China, as we measure it, may be spuriously correlated with similarity to other countries. Moreover, if the findings are driven by some common shock to emerging economies, then we would not expect to find any special impact of socio-economic similarity to China — similarity to other emerging markets would also be correlated with a rise in entrepreneurial activity. To investigate this, we successively compute the similarity of each $country * sector$ to its counterpart in *every* other country. We then successively re-estimate Equation 2 in which we replace $ChinaSuitability_{cs}$ with the analogous suitability measure for every other country. Figure 5a 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.

A second potential concern is that our measure of China suitability may be very similar for all sectors in each country. The results may consequentially not be capturing differences in sector-specific appropriateness of Chinese entrepreneurship within each country. To address this question, we again estimate a series of placebo versions of Equation 2, now randomizing the sectoral component of $ChinaSuitability_{cs}$ within each country.[39] Figure 5b presents the histogram of these placebo coefficients and our baseline coefficient

[37]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 of the two-year window 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." In the end, we are able to identify the "surge year" for 108 out of the 129 China-led sectors. Unidentified sectors and non-China-led sectors are assigned the year of 2013 to be consistent with the baseline analysis. Appendix Figure A.10 shows the number of Chinese deals over time for several example sectors, with the surge year marked by a vertical line.

[38]When sectors are pooled together, 2013 also satisfies the requirements used to determine the sector-specific surge year described in the previous footnote.

[39]For example, for the AgTech macro-sector in Pakistan, we assign the China suitability score of one of Pakistan's 15 major sectors at random.

estimate as a vertical red line. Our estimate is again larger than all placebo estimates, suggesting that our suitability measure is not only capturing broad differences in similarity to China across countries, but also within-country differences in similarity to China across investment sectors.

A final potential concern is that the timing of investment growth after 2013 captures, in part, aggregate trends and not the fact that investment follows sectors as they emerge in China. To address this question, we follow the method outlined above to identify a surge year for investment in China for each sector ($Post_{st}$). We then estimate a series of regressions after randomizing the surge year across China-led sectors (but maintaining the same number of sectors assigned to each year). The distribution of these estimates is displayed in Figure 5c as a green histogram. Our estimate from this specification, using the actual surge year for each sector, is marked with a vertical red line in the far right tail of the distribution. These estimates show that the rise in venture activity in China-led sectors exactly followed the sector-level timing of growth in China.

4.2.2 Exogenous shocks to Chinese leadership

As an alternative empirical strategy, we exploit the emergence of successful companies in China early in the sample period as shifters of sector-level leadership. Our motivation for this analysis is the likelihood that there is an element of path dependency in which sectors China leads: those where the nation achieved earlier entrepreneurial success are likely to attract considerable attention and additional investment. Furthermore, there is an element of randomness in which sectors China had early success. An extensive entrepreneurial finance literature suggests that the most critical criterion for venture success is neither the nature of the business plan nor the market, but rather the caliber of the entrepreneurial founder(s) (Bernstein et al., 2017; Gompers et al., 2020). This suggests the exact sectors into which China's earliest success stories fell, and which subsequently attracted follow-on investments, were highly idiosyncratic and plausibly independent from sector-level trends across emerging markets.

To define early successes in China, we identify all companies in China that raised a financing round either greater than US$50 million or above US$100 million in size prior to 2008.[40] Columns 1 and 2 of Table A.15 show that the number of these early successes strongly predicts whether or not a sector becomes one of the "China-led" sectors by our definition. In columns 3 through 6 of Table A.15, we repeat the baseline estimates from

[40]Large financing rounds are likely to be associated with high valuations. Data coverage is much better for financing round size than that for valuations. Therefore, we use large financing as proxies for unicorn firms (defined as those with a nominal valuation of greater than one billion dollars (Davydova et al., 2022)).

Tables A.3 and 2, replacing the China-led indicator with each of the two measures of early Chinese success. The results are strongly positive and significant in all specifications, consistent with a causal interpretation of our baseline results.

4.3 Magnitudes

To investigate the overall impact of China's rise on venture activity, we use our baseline specification (Equation 2) to predict the total number of deals in emerging markets, both with and without the effect of China.[41] We find that the rise of China increased emerging market venture deals by 42% using our baseline China-led measure and 26% using our strict China-led measure (see Appendix D for details). This number is substantial and also likely underestimates the true effect, since our suitability measure is an imperfect proxy for the appropriateness of Chinese technology and business ideas.

A related counterfactual question is what might have been the impact if a country other than China grew over the past decade in China's place? This could be informative for benchmarking the effect of China *per se* against the potential effect of growth in any other emerging market. We construct our suitability measure for all countries and, using our estimate of β and the fixed effects in Equation 2, predict how many deals would have taken place in each emerging economy if each other country had risen in China's place.[42] To incorporate the potential scale of innovation in each country, we also report results after scaling the number of sectors "led" by each country by its GDP relative to that of China. To facilitate cross-country comparisons, we focus on the strict China-led measure.[43] Without scaling by GDP, the country that generates the largest increase in emerging market deals (36%) is Pakistan, followed by Indonesia and Nigeria. These estimates are driven by the fact that these countries are, by our measure, the most "similar" to the highest number of other emerging market country-sector pairs. This finding is consistent with our point in the Introduction that Chinese technology may not be best suited to other emerging markets in absolute terms. When we scale by GDP — taking into account the fact that China's dominance across so many sectors was, in part, due to its size

[41] 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 below 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 suitability takes value zero, and we adjust our suitability measure so that this is the case for the minimum value of the suitability measure within each macro-sector. 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.

[42] 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.

[43] We describe this exercise in more detail in Appendix D.

— China's 26% is at the top of the list. The country in distant second is Japan (at 9%). Appendix Table A.16 lists countries that could have the largest positive effect on emerging market venture capital, according to our estimates.

4.4 Dynamics

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

We begin with sectors subsequently led by China. Figure 6 reports the relationship between entrepreneurship in China-led sectors and each decile of the suitability measure, separately for the pre-period (before 2013) and post-period (after 2013).[44] The first decile is the excluded group and all bars display estimates of the interaction between $ChinaLed_s$ and the appropriate decile indicator. Figure 6a shows that there is no difference between country-sector pairs with different values of the suitability index prior to the rise of China: the effect of each decile is small in magnitude and statistically indistinguishable from zero. Figure 6b shows that after 2013, there is a positive relationship between the suitability decile and venture activity; with two exceptions, the bars increase moving from left to right.

We next investigate the role of the US during the pre-period. We construct a country-by-sector measure of similarity to the US ($USSuitability_{cs}$), following procedures analogous to the measure of $ChinaSuitability_{cs}$. We then examine whether similarity to the US predicts global entrepreneurship at the country-by-sector level prior to the rise of China. Focusing on years before 2013, we estimate:

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

where $USLed_s = 1 - ChinaLed_s$ are the sectors in which the US specializes (compared to China). ϕ_1 captures the effect of US suitability on deals in sectors dominated by US firms prior to the rise of China. ϕ_2 captures the effect of US suitability on deals in sectors that would come to be dominated by Chinese firms.

Figure 7a displays our estimate of ϕ_1. It is positive and significant, consistent with qualitative accounts that during the early part of our sample period, new entrepreneurial ideas came almost exclusively from the US. Thus, in sectors where US firms were active

[44] Rather than split the sample into a pre-period and post-period, Figure A.12 includes a full set of year indicators interacted with $ChinaLed_s * SuitabilityQuintile^q_{cs}$ for $q = 2, ..., 5$, where $SuitabilityQuintile^q_{cs}$ is an indicator that equals one if the suitability score is in quintile q. All sets of country-sector pairs were on very similar trends prior to the rise of China. Starting in 2014 they begin to diverge, with the highest suitability quintile (dark blue) increasing the most. The gap widens over the course of the sample period.

and appropriate "benchmark" companies likely to exist, areas with similar socioeconomic conditions to the US could adopt US business ideas. Figure 7b displays our estimate of ϕ_2. The estimate is about half the magnitude of ϕ_1 and statistically indistinguishable from zero. This result is consistent with less overall activity in these sectors by US firms, even prior to the rise of China (see Figure A.5a). Figures 7c and 7d report analogous estimates of Equation 3 in which US suitability is replaced with China suitability. The estimates are very close to zero and statistically insignificant in both cases, consistent with our more disaggregated pre-trend analysis in Figure 6a showing that socioeconomic similarity to China did not predict entrepreneurship *prior* to the rise of China.

Together, these findings show that the baseline results in Section 4.2 are not driven by any pre-existing trends in entrepreneurial activity prior to the rise of China. Instead, before 2013, socioeconomic similarity to the US was a key determinant of global venture investment, consistent with qualitative evidence suggesting that investors relied almost exclusively on successful benchmark companies from the US during this period.

Finally, we investigate whether the effect of socioeconomic similarity to the US changed after 2013. Figure A.13 reports difference in the effect of $(USSuitability_{cs} * USLed_s)$ and $(USSuitability_{cs} * ChinaLed_s)$ during the pre-period vs. post-period.[45] If anything, the effect of socioeconomic similarity to the US *increases* during the post period for US-led sectors, although the effect is not significant. These estimates suggest that even after China's rise to global prominence, entrepreneurial diffusion from the US to similar country-sector pairs did *not* decline, and business development continued in US-led sectors around the world. In other words, China's rise did not replace the US's role; instead, it offered a set of alternative potential business models in new sectors and 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.

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

In order to capture emulation of Chinese companies, we use Natural Language Processing (NLP) tools to measure similarity in business description across all company pairs within each sector.[46] We then calculate the pairwise similarity for all companies in each sector. This method captures patterns consistent with case study analysis. For example, as previously discussed, Byju's from India and Yuanfudao from China are both in the EdTech sector "Solutions for Primary and Secondary Students," and a range of investors and analysts have noted that Byju's drew inspiration from the business model pioneered by Yuanfudao. Consistent with this, using the two companies' descriptions, we estimate a high (80.11%) level of textual similarity between Byju's and Yuanfudao (see Section 2.2). However, Byju's is not similar to *all* Chinese companies in the same sector. For example, it has a very low level of textual similarity (28.59%) to Yundee, a Chinese 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 in the sector) but not be similar to others. We then estimate versions of Equation 2 with these within-sector measures of companies' similarity to China as the dependent variables.

Table 4 presents the results. We estimate that China-suitable country-sector pairs increase average within-sector business model 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). Thus, not only did suitable country-sector pairs grow in response to the rise of China, but companies in these sectors became more similar to their Chinese counterparts in the same sector. For a given level of socioeconomic suitability, 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.

[46] Specifically, we use SentenceTransformer tokenizer, a framework for state-of-the-art sentence embeddings, with pre-trained BERT models to tokenize business descriptions and calculate pairwise cosine similarity. The SentenceTranformer framework is especially suitable for textual similarity comparisons because the resulting embeddings are directly comparable for cosine similarity calculations while also being computationally more efficient than directly using BERT.

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 5, columns 1-3, reports estimates in which the dependent variables are the number of deals with an investor from China (column 1), the number of deals with an investor from the US (column 2), and the number of deals with a local investor (column 3). 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 or globally connected investors "pile in" to finance existing firms once there is a proven benchmark in China.

Table 5, 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 socioeconomic "appropriateness," but they have been silent about the role of politics. Politics may also play a central role in determining which technologies get developed in China and how they diffuse around the globe (e.g., Beraja et al., 2023a). It is possible, for example, that our main findings are, in part, capturing disproportionate technology diffusion to China's political allies, which could be driven by strategic geopolitical considerations or business sharing agreements. The direction of entrepreneurship in China has also been driven in part by top-down initiatives that target key strategic sectors. It is possible that these political initiatives are responsible for the development of some of the business models that end up diffusing to emerging markets.

To investigate these questions, we develop two proxies for political closeness to China: *(i)* voting similarity on UN resolutions, which captures countries' international political stance;[47] 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.[48] 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 2, 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 6 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

[47]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.

[48]Using a scale from -10 to 10, the Polity score determines where a country stands on the spectrum from authoritarianism to full democracy.

Equation 2 in which we also include $ChinaLed_s * Post_t$ interacted with both UN voting distance from China and Polity score distance to China (see Table A.17). The coefficient on both terms is negative, indicating that countries more politically aligned with China are more likely to invest in China-led sectors. However, the inclusion of these variables does not affect our main coefficient of interest, indicating that the diffusion of economically "appropriate entrepreneurship" operates independently from political ties.

6 Broader impacts

In this section, we investigate the broader economic impacts of this rise in emerging market entrepreneurship. On the one hand, by choosing a more appropriate set of entrepreneurial models, new ventures may be able to become more innovative and lead to economic growth. On the other, if entrepreneurs are simply substituting one successful model of new venture activity for another, the importance 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? To investigate this question, 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 acquisition or IPO (a rough but frequently used proxy for the success of venture investments), and firms that have not yet exited.

Table 5, columns 6-8 present estimates of Equation 2 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 (Lafontaine and Shaw, 2016; Shaw and Sørensen, 2019) 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:

$$y^X_{cst} = \beta\,(ChinaLed_s * Post_t * ChinaSuitability_{cs}) + \alpha_{cs} + \gamma_{ct} + \delta_{st} + \epsilon_{cst}, \tag{4}$$

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.[49] 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.[50]

Table 7 reports estimates of Equation 4. Column 1 shows that the rise of China led to a larger group of serial entrepreneurs in other emerging markets. 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

[49]To identify the founder(s) of each company, we search the lists of contacts associated with each company and identify individuals with "founder" in their title. If no contact has "founder" in their title, we define the founder as the CEO when the company had its first deal.

[50]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.

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 or path forward. 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.

We repeat this analysis focusing on serial investors. Appendix Table A.18 follows the same structure as Table 7, except all outcomes focus on serial investors instead of serial entrepreneurs. These findings are less clear: the coefficient estimates are all positive, but 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 first developed in China may also extend their investments in subsequent years to local businesses in other areas.

6.3 City-level effects and geographic spillovers

So far, we have focused on country-by-sector-level variation in exposure to the rise of Chinese VC. 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 emerging market entrepreneurship accompanied by the growth of geographic hubs of entrepreneurship and innovation in emerging markets?

To measure the exposure of each city around the world to the rise of China, we measure the share of VC-backed companies in the city that are in one of the China-led sectors during the pre-analysis period. We then investigate whether the rise of China boosted VC-backed company formation in these locations that were best able to capitalize the growth of China. We estimate:

$$y_{it} = \gamma(ShareChinaLed_i * Post_t) + \alpha_i + \delta_t + \epsilon_{it} \tag{5}$$

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.[51] The findings are reported in Table 8. In Panel A, all outcomes are

[51] We geo-locate the headquarters of all PitchBook companies using SimpleMaps data and supplement it

normalized counts; in Panel B, they are inverse hyperbolic sine transformed; and in Panel C, they are logged. We first restrict attention to cities in emerging economies.

In Table 8, column 1, the outcome is the number of new companies. We estimate that γ is positive and significant in all panels. 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. The result from column 1 could be entirely driven by the growth of sectors dominated by China. However, if there are local geographic spillovers from China-inspired entrepreneurship, we may also find positive effects on companies that are not in sectors led by China. While intuitively the effect size is larger for companies in China-led sectors (column 2), it is positive and statistically distinguishable from zero 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 include an interaction between $ShareChinaLed_i * Post_t$ and the emerging market indicator in our estimate of Equation 5 and find that the triple-interaction is positive and significant while the un-interacted term is small (and in Panels B and C, statistically indistinguishable from zero). Thus, consistent with all preceding analyses, the growth of Chinese venture activity had little effect, if any, in developed countries, but a large effect in developing ones.

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 in all three panels, and is statistically distinguishable from zero in Panels A and C. 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.[52]

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

with Opendatasoft. We use patents' location information from disambiguated assignee locations compiled by PatentsView. We link each company and patent to the nearest populated city from Natural Earth. We restrict attention for our analysis to cities with at least 20 companies founded during the pre-analysis period, so that we have a reasonable amount of data to measure $ShareChinaLed_i$. In total, the analysis consists of 284 cities in 63 countries.

[52] Figure A.14 reports event study estimates corresponding to the specifications from columns 1, 2, 3, and 5 of Panel A. 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 2014/2015 and the gap widens thereafter.

follow China, there was substantial business formation, including in sectors that were *not* dominated by China. There was also a substantial 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, these (locally suited) new firms, business models, and technologies may improve people's lives: greater VC 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 next 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 2 to predict the total number of deals in each country-sector pair during our post-period driven 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:

$$y_{cm} = \phi PredictedDeals_{cm} + \alpha_c + \delta_m + \epsilon_{cm}, \tag{6}$$

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 6 are reported in Appendix Table A.19. 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 predicted increase in entrepreneurial activity 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% and is more precisely estimated. Columns 3-4 repeat the specifications from columns 1-2 except they restrict attention to macro-sectors of agricultural technology, education technology, and health technology (enterprise and retail) — areas in which we can most clearly track improvements in well-being using the WDI database. The coefficient estimates increase by roughly 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 VC-backed 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 systematically 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 US-led system. This hypothesis is not unique to the rise of China. As technology investment increases in India, for example, it too may have consequences far beyond India's borders by developing technologies that are appropriate for other low-income regions. Brazil's dramatic 20th century rise in agricultural productivity was fueled, in part, by major investments in innovation tailored toward Brazil's ecology (Correa and Schmidt, 2014). A long-standing collaboration between Brazilian and African agricultural research organizations is based on the premise that these technologies could benefit parts of Africa, where ecological conditions are similar.[53] 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 the ultimate 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. The first is to understand the political and geo-political consequences of the rise of Chinese innovation. The entrepreneurial success of Chinese business models may also lead to more credibility for "the Chinese model," at the expense of US or Western influence. Israel's entrepreneurial success, for instance, has long been reputed to give it more influence on the global stage than a country with a similar GDP and population would enjoy otherwise (Senor and Singer, 2009). Understanding the consequences of Chinese entrepreneurial success and its diffusion for "soft power" is an important question.[54]

Second, our study ends in 2020, which may have marked 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.[55] 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.

A third question is the extent to which the diffusion of business ideas to the developing world may be accelerated by the growing importance of venture capital-funded entrepreneurship. Innovation in new ventures may flow more easily across national boundaries than corporate R&D. 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. Moreover, 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 global diffusion of business models and innovation.

[53] See here: https://www.embrapa.br/en/cooperacao-tecnica/m-boss.

[54] A related concern is that, in recent years, VC investment has fueled innovation that accelerated the development of Chinese military technology. For a recent discussion, see this report by the US House of Representatives: https://selectcommitteeontheccp.house.gov/sites/evo-subsites/selectcommitteeontheccp.house.gov/files/evo-media-document/2024-02-08%20FINAL%20VC%20Report.pdf

[55] The quote is from https://www.ft.com/content/1d288c2f-215a-4661-aa1a-273671b945cd. For a more general discussion of shifting Chinese venture policy, see https://www.economist.com/business/2022/06/27/the-rise-of-chinas-vc-industrial-complex.

References

Acemoglu, Daron and Fabrizio Zilibotti, "Productivity differences," *Quarterly Journal of Economics*, 2001, *116* (2), 563–606.

Aghion, Philippe, Celine Antonin, Luc Paluskiewicz, David Stromberg, Xueping Sun, Rafael Wargon, and Karolina Westin, "Does Chinese research hinge on US coauthors? Evidence from the China Initiative," *Working Paper No. 1936, Centre for Economic Performance, London School of Economics*, 2023.

_, Jing Cai, Mathias Dewatripont, Luosha Du, Ann Harrison, and Patrick Legros, "Industrial policy and competition," *American Economic Journal: Macroeconomics*, 2015, *7* (4), 1–32.

Akcigit, Ufuk, Emin Dinlersoz, Jeremy Greenwood, and Veronika Penciakova, "Synergizing ventures," *Journal of Economic Dynamics and Control*, 2022, *143*, 104427.

_, Sina T. Ates, Josh Lerner, Richard R. Townsend, and Yulia Zhestkova, "Fencing off Silicon Valley: Cross-border venture capital and technology spillovers," *Journal of Monetary Economics*, 2024, *141* (1), 14–39.

Atkin, David, Arnaud Costinot, and Masao Fukui, "Globalization and the ladder of development: Pushed to the top or held at the bottom?," *Working Paper No. 29500, National Bureau of Economic Research*, 2021.

Ayyagari, Meghana, Asli Demirguc-Kunt, and Vojislav Maksimovic, "What determines entrepreneurial outcomes in emerging markets? The role of initial conditions," *Review of Financial Studies*, 2017, *30* (7), 2478–2522.

Bai, Jie, Panle Jia Barwick, Shengmao Cao, and Shanjun Li, "Quid pro quo, knowledge spillover, and industrial quality upgrading: Evidence from the Chinese auto industry," *Working Paper No.27664, National Bureau of Economic Research*, 2022.

Bailey, Michael A., Anton Strezhnev, and Erik Voeten, "Estimating dynamic state preferences from United Nations voting data," *Journal of Conflict Resolution*, 2017, *61* (2), 430–456.

Barro, Robert J. and Xavier Sala i Martin, "Technological diffusion, convergence, and growth," *Journal of Economic Growth*, 1997, *2* (1), 1–26.

Basu, Susanto and David N. Weil, "Appropriate technology and growth," *Quarterly Journal of Economics*, 1998, *113* (4), 1025–1054.

Beraja, Martin, Andrew Kao, David Y. Yang, and Noam Yuchtman, "Exporting the surveillance state via trade in AI," *Unpublished Working Paper*, 2023.

_, David Y. Yang, and Noam Yuchtman, "Data-intensive innovation and the state: Evidence from AI firms in China," *Review of Economic Studies*, 2023, *90* (4), 1701–1723.

Bernstein, Shai, Arthur Korteweg, and Kevin Laws, "Attracting early-stage investors: Evidence from a randomized field experiment," *Journal of Finance*, 2017, *72* (2), 509–538.

__ **, Xavier Giroud, and Richard R. Townsend**, "The impact of venture capital monitoring," *Journal of Finance*, 2016, *71* (4), 1591–1622.

Caselli, Francesco and Wilbur J. Coleman, "The world technology frontier," *American Economic Review*, 2006, *96* (3), 499–522.

Chen, Jun, "Venture capital research in China: Data and institutional details," *Journal of Corporate Finance*, 2023, *81*, 102239.

Chen, Zhao, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Yi Xu, "Notching R&D investment with corporate income tax cuts in China," *American Economic Review*, 2021, *111* (7), 2065–2100.

Colonnelli, Emanuele, Bo Li, and Ernest Liu, "Investing with the government: A field experiment in China," *Journal of Political Economy*, 2023, *forthcoming.*

Comin, Diego and Bart Hobijn, "An exploration of technology diffusion," *American Economic Review*, 2010, *100* (5), 2031–2059.

__ **and Martí Mestieri**, "Technology diffusion: Measurement, causes, and consequences," in Philippe Aghion and Steven N Durlauf, eds., *Handbook of Economic Growth*, Vol. 2, New York: Elsevier, 2014, pp. 565–622.

__ **and** __ , "If technology has arrived everywhere, why has income diverged?," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 137–178.

Correa, Paulo and Cristiane Schmidt, "Public research organizations and agricultural development in Brazil: How did Embrapa get it right?," *Economic Premise*, 2014, *145*, 1–10.

Costinot, Arnaud, Dave Donaldson, Margaret Kyle, and Heidi Williams, "The more we die, the more we sell? A simple test of the home-market effect," *Quarterly Journal of Economics*, 2019, *134* (2), 843–894.

Davydova, Daria, Rüdiger Fahlenbrach, Leandro Sanz, and René M. Stulz, "The unicorn puzzle," *Working Paper No. 30604, National Bureau of Economic Research*, 2022.

Eaton, Jonathan and Samuel Kortum, "Technology, geography, and trade," *Econometrica*, 2002, *70* (5), 1741–1779.

Fang, Lily H., Josh Lerner, and Chaopeng Wu, "Intellectual property rights protection, ownership, and innovation: Evidence from China," *Review of Financial Studies*, 2017, *30* (7), 2446–2477.

Giorcelli, Michela, "The long-term effects of management and technology transfers," *American Economic Review*, 2019, *109* (1), 121–152.

Gompers, Paul A. and Josh Lerner, *The Venture Capital Cycle*, Cambridge: MIT Press, 1999.

— **, Anna Kovner, Josh Lerner, and David Scharfstein**, "Performance persistence in entrepreneurship," *Journal of Financial Economics*, 2010, *96* (1), 18–32.

— **, Will Gornall, Steven N. Kaplan, and Ilya A. Strebulaev**, "How do venture capitalists make decisions?," *Journal of Financial Economics*, 2020, *135* (1), 169–190.

Haltiwanger, John, Ron S. Jarmin, and Javier Miranda, "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 2013, *95* (2), 347–361.

Holmes, Thomas J., Ellen R. McGrattan, and Edward C. Prescott, "Quid pro quo: Technology capital transfers for market access in China," *Review of Economic Studies*, 2015, *82* (3), 1154–1193.

Jaffe, Adam B, Manuel Trajtenberg, and Rebecca Henderson, "Geographic localization of knowledge spillovers as evidenced by patent citations," *Quarterly Journal of Economics*, 1993, *108* (3), 577–598.

Kaplan, Steven N. and Josh Lerner, "Venture capital data: Opportunities and challenges," in John Haltiwanger, Erik Hurst, Javier Miranda, and Antoinette Schoar, eds., *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, Vol. 75 of *National Bureau of Economic Research Studies in Income and Wealth*, Chicago: University of Chicago Press, 2017, pp. 413–431.

Keller, Wolfgang, "Geographic localization of international technology diffusion," *American Economic Review*, 2002, *92* (1), 120–142.

— , "International technology diffusion," *Journal of Economic Literature*, 2004, *42* (4), 752–782.

Kortum, Samuel and Josh Lerner, "Assessing the impact of venture capital on innovation," *RAND Journal of Economics*, 2000, *31* (4), 674–692.

Kremer, Michael, "Pharmaceuticals and the developing world," *Journal of Economic Perspectives*, 2002, *16* (4), 67–90.

— **and Rachel Glennerster**, *Strong Medicine: Creating Incentives for Pharmaceutical Research on Neglected Diseases* 2004.

König, Michael, Kjetil Storesletten, Zheng Song, and Fabrizio Zilibotti, "From imitation to innovation: Where is all that Chinese R&D going?," *Econometrica*, 2022, *90* (4), 1615–1654.

Lafontaine, Francine and Kathryn Shaw, "Serial entrepreneurship: Learning by doing?," *Journal of Labor Economics*, 2016, *34* (S2), S217–S254.

Lee, Keun and Chaisung Lim, "Technological regimes, catching-up and leapfrogging: Findings from the Korean industries," *Research Policy*, 2001, *30* (3), 459–483.

Lerner, Josh, Amit Seru, Nick Short, and Yuan Sun, "Financial innovation in the 21st century: Evidence from US patents," *Journal of Political Economy*, 2023, *forthcoming.*

— **and Antoinette Schoar**, "Does legal enforcement affect financial transactions?: The contractual channel in private equity," *Quarterly Journal of Economics*, 2005, *120* (1), 223–246.

— **and Ramana Nanda**, "Venture capital's role in financing innovation: What we know and how much we still need to learn," *Journal of Economic Perspectives*, 2020, *34* (3), 237–61.

Mallaby, Sebastian, *The Power Law: Venture Capital and the Art of Disruption*, New York: Penguin UK, 2022.

Moscona, Jacob and Karthik Sastry, "Inappropriate technology: Evidence from global agriculture," *Unpublished Working Paper, Harvard University*, 2023. https://ssrn.com/abstract=3886019.

Parente, Stephen L and Edward C Prescott, "Barriers to technology adoption and development," *Journal of Political Economy*, 1994, *102* (2), 298–321.

— **and** — , *Barriers to Riches*, Cambridge: MIT Press, 2002.

Puri, Manju and Rebeca Zarutskie, "On the lifecycle dynamics of venture-capital- and non-venture-capital-financed firms," *Journal of Finance*, 2012, *67* (6), 2247–2293.

Retterath, Andre and Reiner Braun, "Benchmarking venture capital databases," *Unpublished Working Paper*, 2022. https://ssrn.com/abstract=4045772.

Samila, Sampsa and Olav Sorenson, "Venture capital, entrepreneurship, and economic growth," *Review of Economics and Statistics*, 2011, *93* (1), 338–349.

Senor, Dan and Saul Singer, *Start-up Nation: The Story of Israel's Economic Miracle*, New York: Twelve, 2009.

Shaw, Kathryn and Anders Sørensen, "The productivity advantage of serial entrepreneurs," *ILR Review*, 2019, *72* (5), 1225–1261.

Tonby, Oliver, Jonathan Woetzel, Noshir Kaka, Wonsik Choi, Anand Swaminathan, Jeongmin Seong, Brant Carson, and Lily Ma, "How Asia can boost growth through technological leapfrogging," Technical Report, McKinsey & Company 2020.

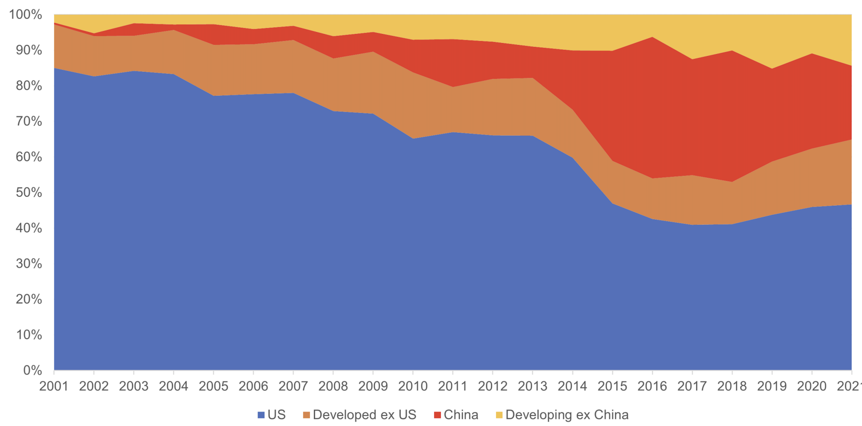
Wei, Shang-Jin, Zhuan Xie, and Xiaobo Zhang, "From 'made in China' to 'innovated in China': Necessity, prospect, and challenges," *Journal of Economic Perspectives*, 2017, *31* (1), 49–70.

Weitzman, Martin L., "Recombinant growth," *Quarterly Journal of Economics*, 1998, *113* (2), 331–360.

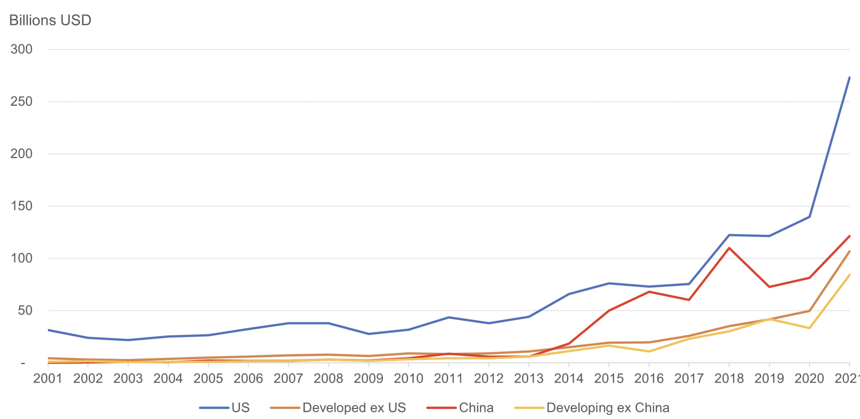
Figures

Figure 1: Venture Investment Overview

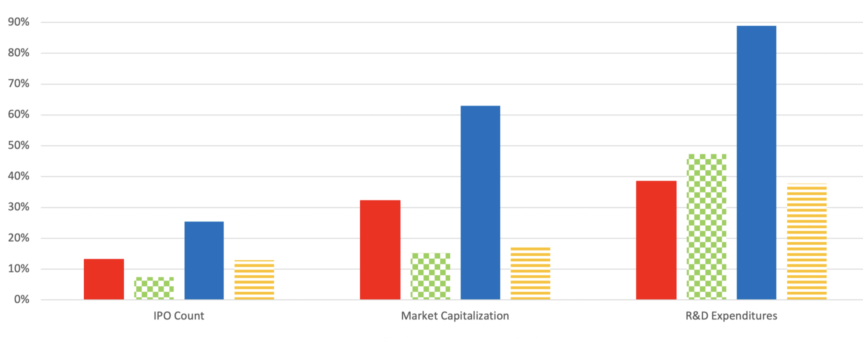
(a) Share of Global VC Investment



(b) Value of Global Investment

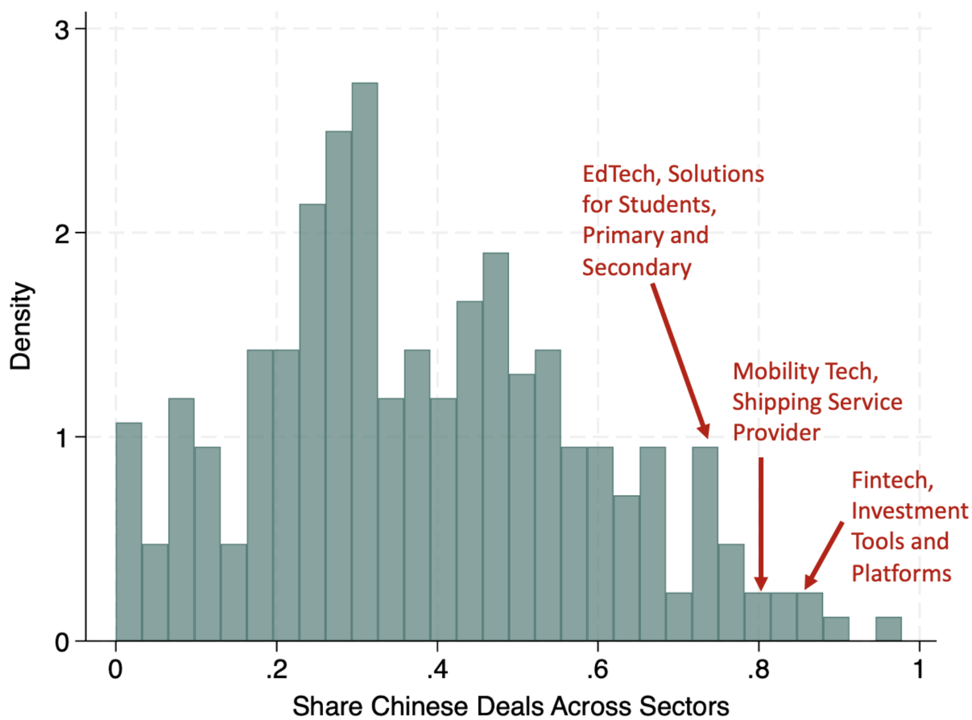


(c) VC-Backed Firms as a Share of Young Public Firms



Notes: 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. The data sources for these figures are discussed in Appendix A.

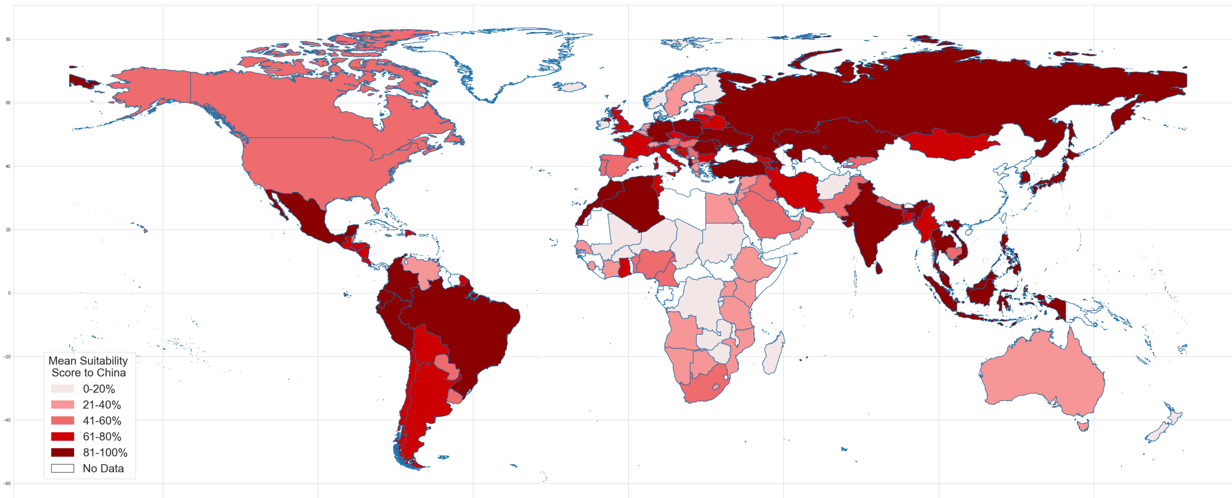
Figure 2: China's Share of Venture Deals Across Sectors



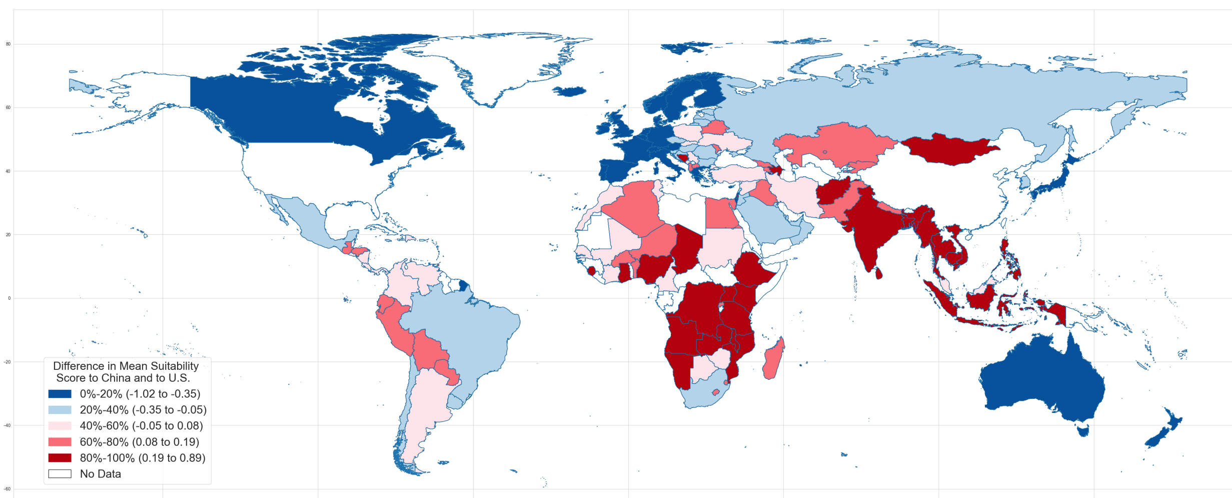
Notes: This figure plots a histogram of the ratio of the number of venture deals for Chinese companies to the total number of venture deals for Chinese and US companies in each sector from 2015 to 2019. Values for three example sectors are marked in red.

Figure 3: Country-Level Variation in Business Suitability

(a) Average China Suitability



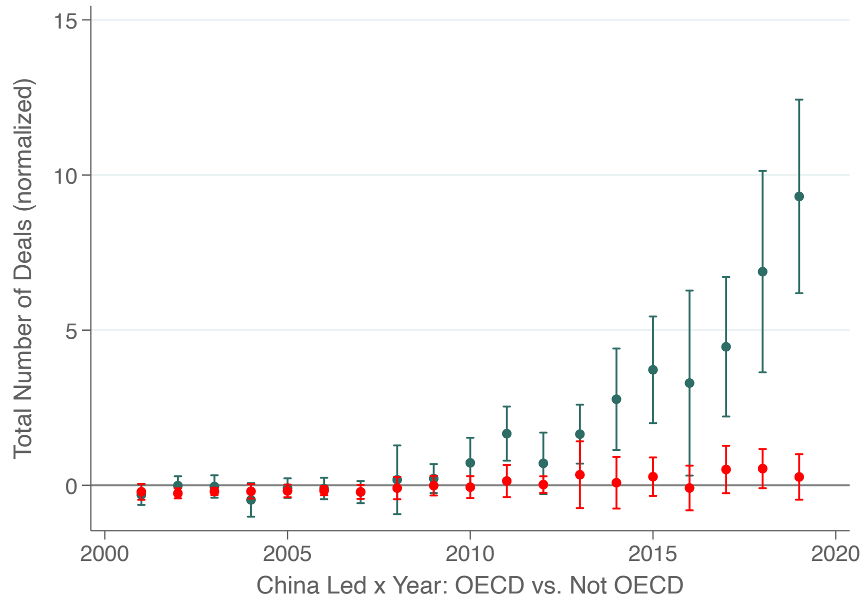
(b) Difference Between Average China Suitability and Average US Suitability



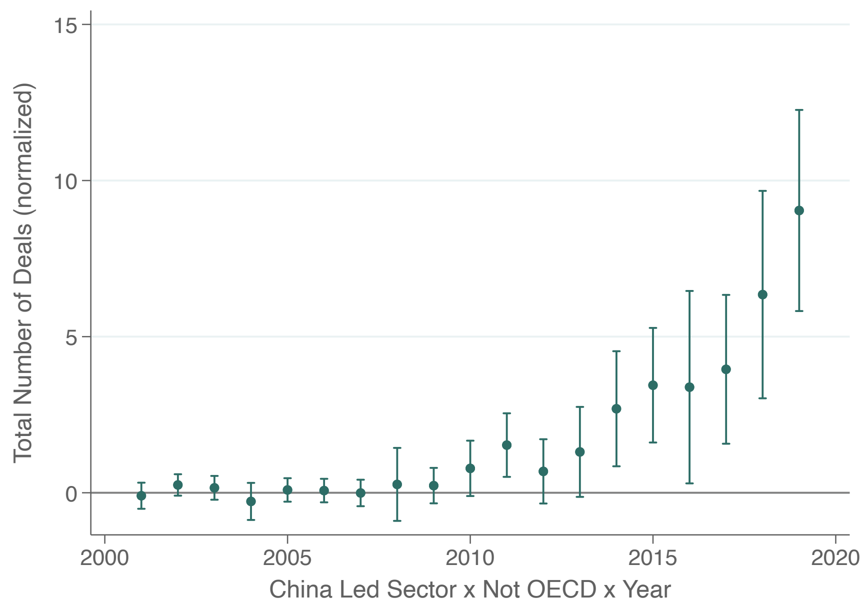
Notes: Figure 3a displays a world map in which each country is color-coded based on its average China suitability, where the average is taken across all fifteen macro-sectors weighted by their share of global pre-period investment. Darker-colored countries are in higher quintiles of the China-suitability distribution. Figure 3b displays a world map in which each country is color-coded based on the difference between average China suitability and average US suitability. 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 4: Dynamic Effects: EM Investments Follow China

(a) Double-Difference Estimates



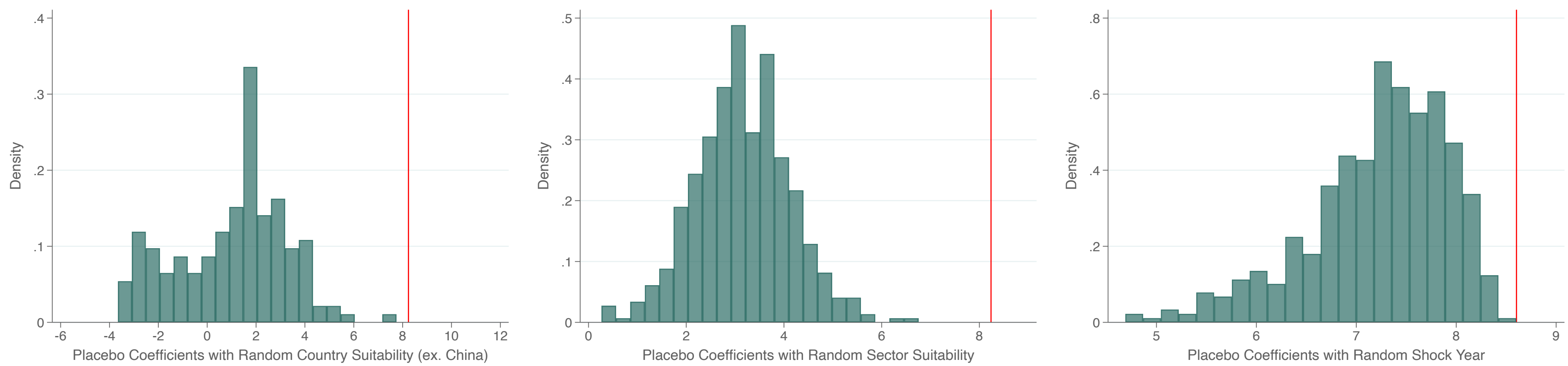
(b) Triple-Difference Estimates



Notes: Figure 4a shows estimates of year indicators interacted with $ChinaLed_s$, separately for countries in the OECD by 1980 (red) and countries outside the OECD in 1980 (green). Figure 4b displays triple-difference estimates of year indicators interacted with $ChinaLed_s * EM_c$. The year 2000 is the excluded category in both figures. Standard errors are clustered by country and 90% confidence intervals are reported.

Figure 5: Falsification Tests

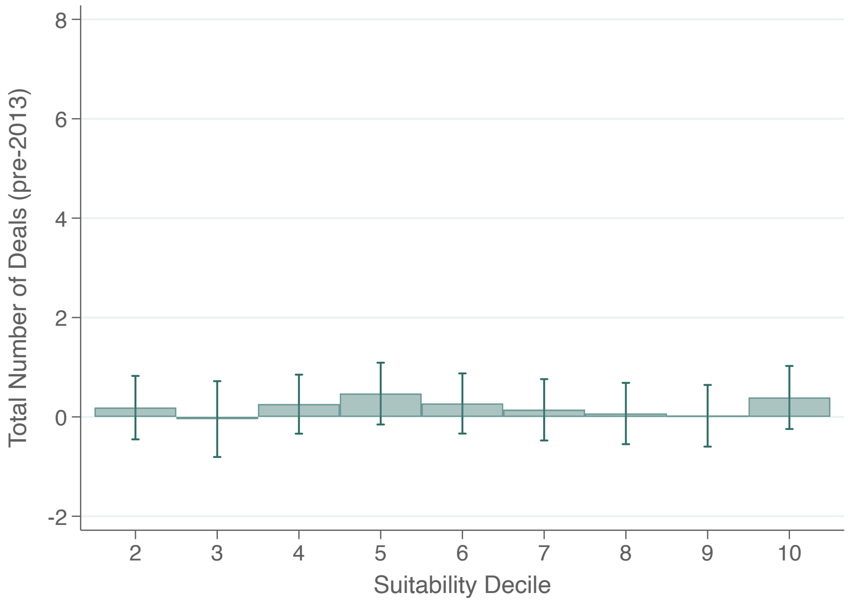
(a) Random Country Suitability Falsification (b) Random Sector Suitability Falsification (c) Random Post-Year Falsification



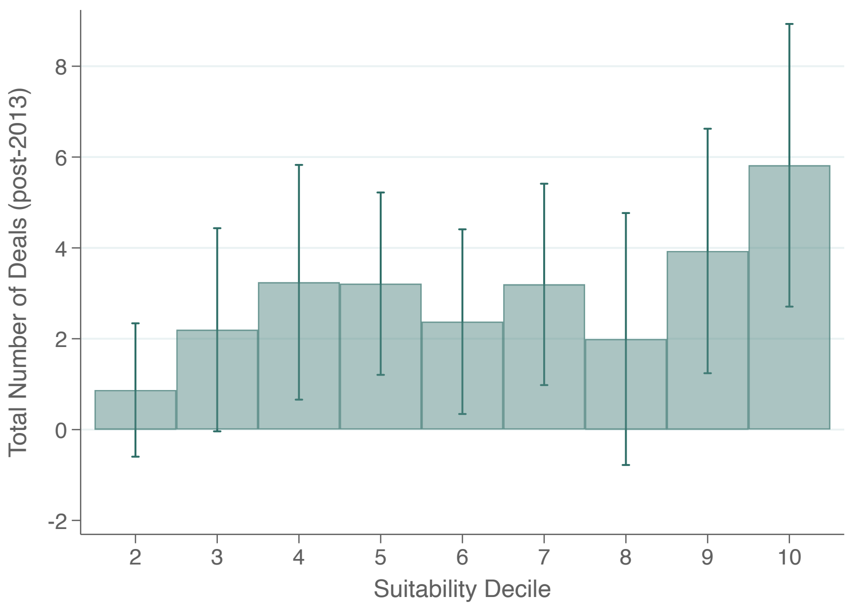
Notes: Figure 5a reports a histogram of coefficient estimates from a series of estimates of Equation 2, in which $ChinaSuitability_{cs}$ is replaced with an analogous suitability measure for each other country. Our main estimate of β from Equation 2 is displayed with a red vertical line. Figure 5b reports a histogram of coefficient estimates from a series of estimates of Equation 2, in which the sector component of $ChinaSuitability_{cs}$ is drawn at random each time. Our main estimate of β from Equation 2 is displayed with a red vertical line. Figure 5c reports a histogram of coefficient estimates from a series of estimates of Equation 2, in which we use a sector-specific post-period identifier and the post-period start year is randomized across sectors. Again, our main estimate of β from using this specification is displayed with a red vertical line. All histograms summarize the results from 500 separate regressions.

Figure 6: Effect of China Suitability by Decile: Pre vs. Post Period

(a) Pre-period (before 2013)



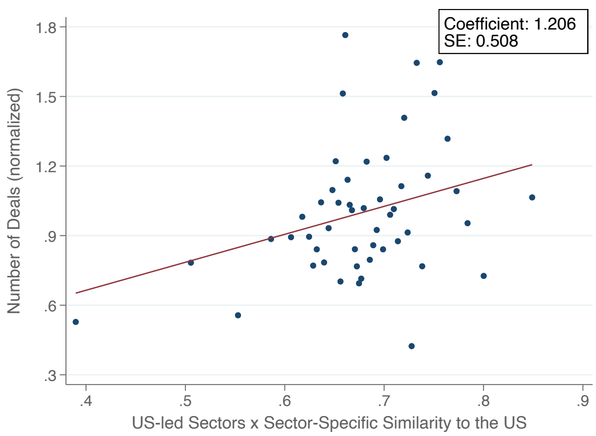
(b) Post-period (after 2013)



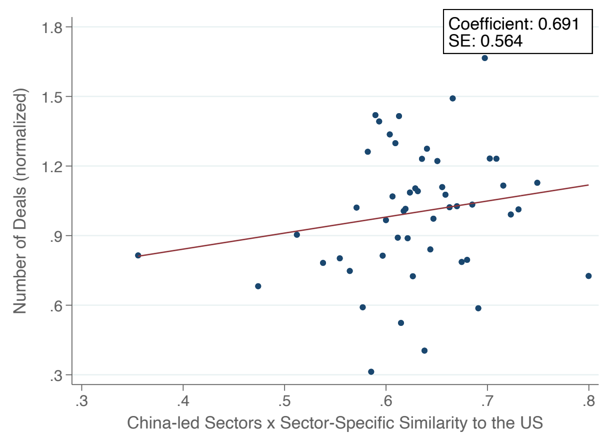
Notes: Figure 6a shows estimates of suitability decile indicators interacted with $ChinaLed_s$. The outcome variable is total (normalized) deals in the country-sector during the pre-period. Figure 6b shows estimates of suitability decile indicators interacted with $ChinaLed_s$. The outcome variable is total (normalized) deals in the country-sector during the post-period. Standard errors are clustered by country and 95% confidence intervals are reported.

Figure 7: China vs. US Suitability, Before China's Rise

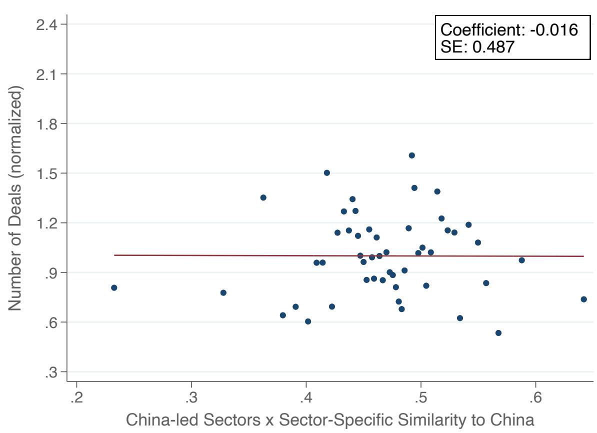
(a) US Suitability × US-Led Sectors



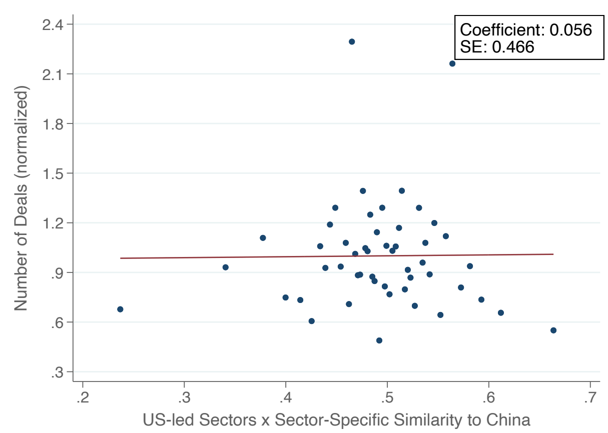
(b) US Suitability × China-Led Sectors



(c) China Suitability × China-Led Sectors



(d) China Suitability × US-Led Sectors



Notes: Figures 7a displays the relationship between pre-2013 deals and $USLed_s \times USSuitability_{cs}$ and 7b displays the relationship between pre-2013 deals and $ChinaLed_s \times USSuitability_{cs}$, both estimated from the same regression. Figure 7c shows the relationship between pre-2013 deals and $ChinaLed_s \times ChinaSuitability_{cs}$ and Figure 7d shows the relationship between pre-2013 deals and $USLed_s \times ChinaSuitability_{cs}$, 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.

Tables

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

Notes: 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.

Table 2: Suitability of Chinese Technology Increases Entrepreneurship

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

Notes: 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.

Table 3: Suitability and Entrepreneurship: Robustness

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	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 Sector (Strict) × Post × China Suitability	11.009***	14.439***	0.133***	0.279***	0.480***
	(3.339)	(4.554)	(0.031)	(0.083)	(0.158)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Suitability × Year FE	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	537600	552300	552300	35507
Mean of Dep. Var	3.588	4.869	0.136	0.184	0.927
SD of Dep. Var	44.979	52.936	0.506	0.803	1.479

Notes: 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. 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. Columns 3 and 4 use inverse hyperbolic sine transformation. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 4: 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 × China Suitability	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

Notes: 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.

Table 5: 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 × China Suitability	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

Notes: 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.

Table 6: The Effect of Political Alignment

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

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

Table 7: Serial Entrepreneurs

	Number of Serial Entrepreneurs				Serial Entrepreneur Indicator			
	(1) All	(2) Only CL Sectors	(3) Any non-CL Sectors	(4) Only non-CL Sectors	(5) All	(6) Only CL Sectors	(7) Any non-CL Sectors	(8) Only non-CL Sectors
China-Led × Post	0.019**	0.005	0.014**	0.006*	0.012***	0.005*	0.009**	0.005*
× China Suitability	(0.008)	(0.003)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
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	0.007	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

Notes: 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 fall 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.

Table 8: 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: Normalized Outcome						
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)
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
Panel B: 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 C: Log Outcome						
Share China-Led × Post	1.762***	1.533***	1.730***	0.352	1.132**	0.052
	(0.553)	(0.562)	(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	1150	602	4714	914	4852
Mean of Dep. Var	1.548	1.989	0.761	1.317	3.400	3.789
SD of Dep. Var	1.199	1.230	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

Notes: 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. Panels A, B, and C report different parameterizations of the outcome variables. Standard errors are clustered by city and year×country, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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

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 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 is 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 and Figure A.2), 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`).

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`.

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.

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.

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).

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, that 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 institutional x 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 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 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 Taiwanese practitioner 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 method delineated by Lerner and Seru (2022), computing the weight to each patent as the average of the number of citations received by the given patent as of September 30, 2023, divided by the mean number of such citations received as of that date by all US patents with a primary assignment to the same four-digit CPC subclass and awarded in the same year.

Appendix B Validation of PitchBook Data

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

Indicator Assignment To construct a country-sector level measure of relative suitability, 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 Appendix Table A.8 and Appendix Table A.9, 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 suitability construction for the baseline, intermediate, and broadest measures, respectively.

To alleviate concerns that these specific missing value-handling criteria might drive our results, in Appendix Table A.10, A.11, A.12, and A.13, we report our main analysis using different criteria to handle missing data: dropping countries with at least 20% or 30% missing values, and dropping indicators with at least 15% or 25% missing values. Reassuringly, all these results are similar to our main specification. As expected, when the thresholds for dropping observations are lower (for example, dropping countries with 20% missing values or dropping indicators with 15% missing values), the estimates are larger than our baseline results.

Appendix D Magnitudes Calculation

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

First, we use our baseline specification (Equation 2) to predict the total number of deals in emerging markets, both with and without the effect of China. This allows us to estimate the size of the increase. We estimate the baseline specification and obtain the coefficients for the interaction term $(ChinaLed_s * Post_t * ChinaSuitability_{cs})$, 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 suitability takes value zero, and we adjust our suitability measure so that this is the case for the minimum value of the suitability measure within each macro-sector. We can adjust this assumption and, predictably, increasing the level of the suitability 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.

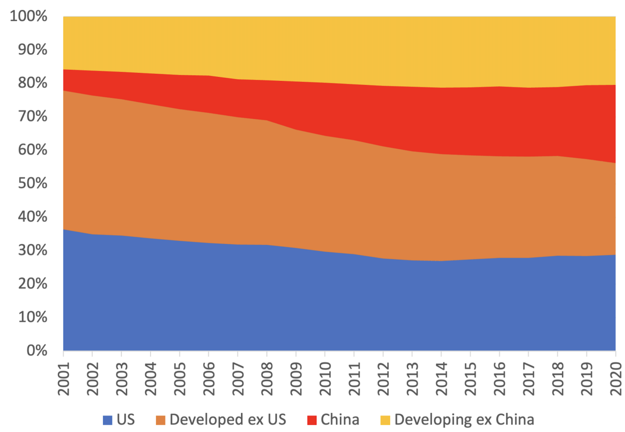
Second, we simulate the hypothetical case of another country X's rise in place of China to evaluate the relative importance of China's rise. We show two versions of the calculation: (i) with a fixed number of country-led sectors and (ii) with a GDP-adjusted number of country-led sectors, where we scale 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 $ChinaSuitability_{cs}$ measure with $XSuitability_{cs}$, which is the our measure of suitability 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 Appendix Table A.16, we list countries with the highest percentage increase in this simulation exercise.

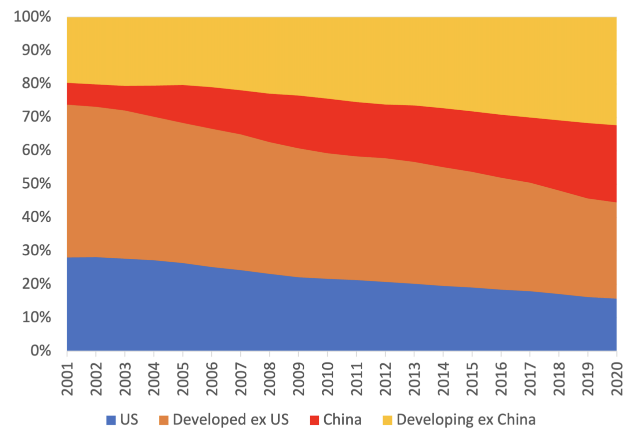
Appendix E Additional Figures and Tables

Figure A.1: Global Innovation Overview

(a) Share of Global R&D Investment

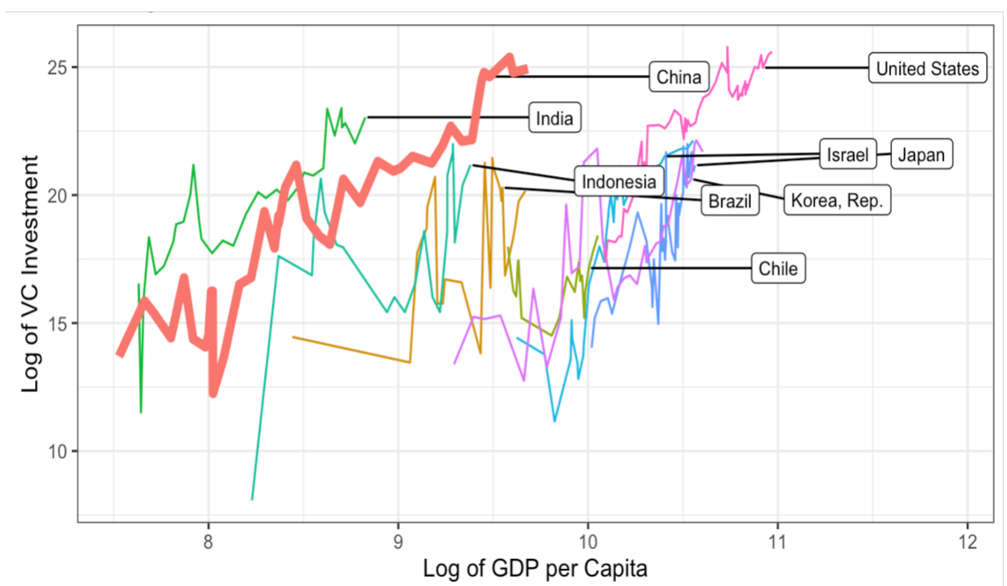


(b) Share of Global Scientific Publications



Notes: 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.

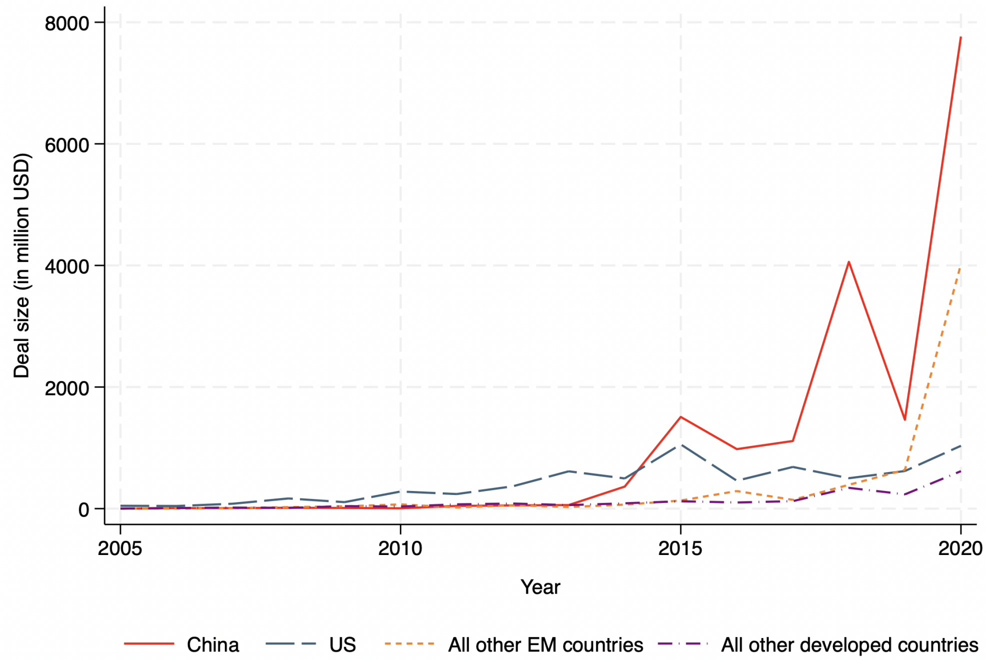
Figure A.2: Venture Investment and GDP Per Capita



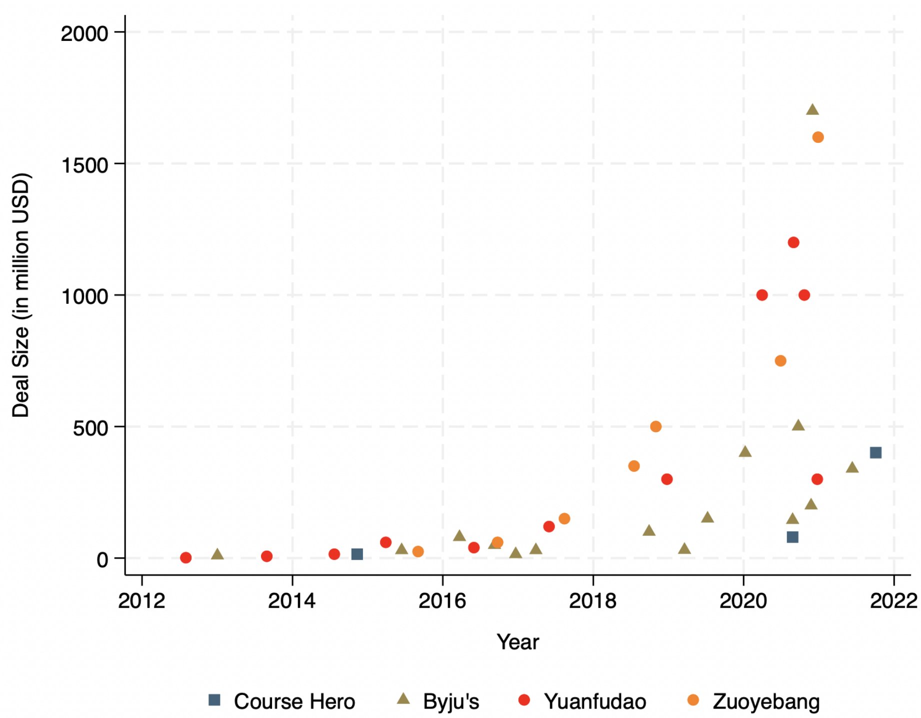
Notes: This figure shows countries' growth in terms of GDP per capita and their venture investment over as long a time period as the data permit. The data sources for this figure are discussed in Appendix A.

Figure A.3: Example Sector: Education Technology for Primary and Secondary Students

(a) Cumulative Annual Transaction Volume

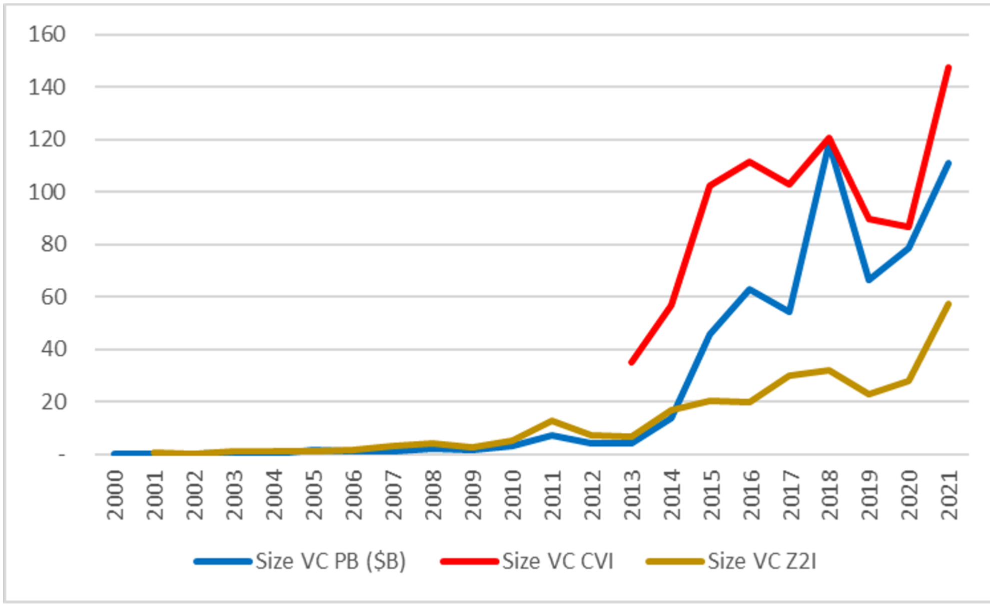


(b) Scatter Plot of Deal Size and Deal Date



Notes: Figure A.3a displays the cumulative annual transaction volume for China, US, all other emerging countries, and all other developed countries for the sector "Education Technology for Primary and Secondary Students." Figure A.3b shows all funding deals for four major companies in the sector, where each dot represents a deal. The companies are listed at the bottom of the sub-figure.

Figure A.4: Cross Validation of Chinese VC Data

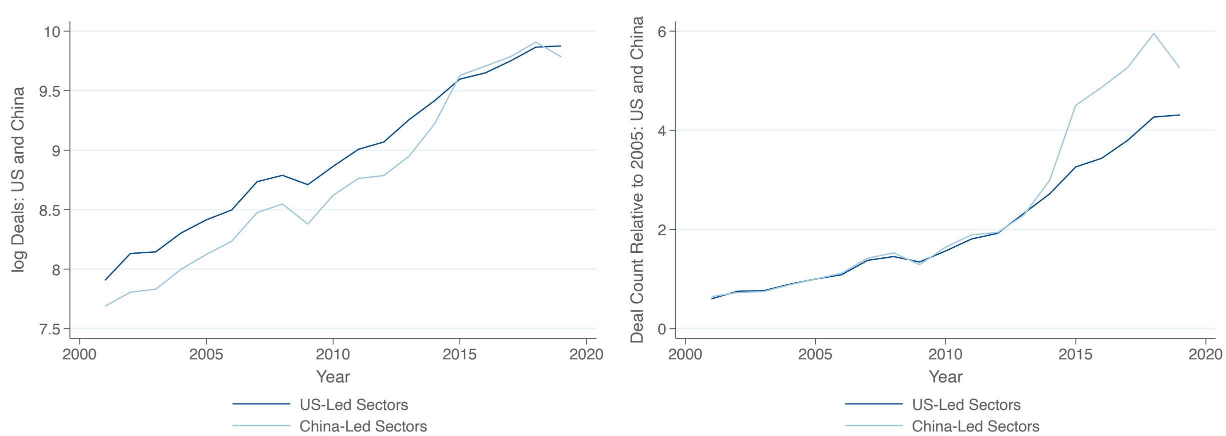


Notes: This figure shows VC transactions in China for three sources: PitchBook, Zero2IPO, and China Venture Institute. Further discussion of the data validation process is in Appendix B.

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

(a) log Deal Count

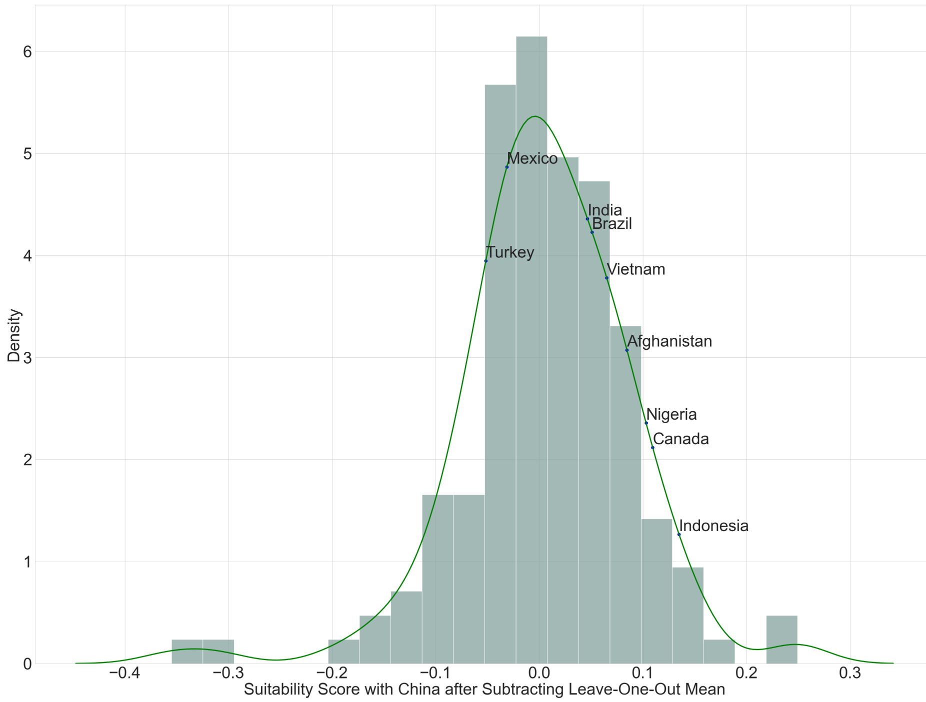
(b) Deal Count Relative to 2005



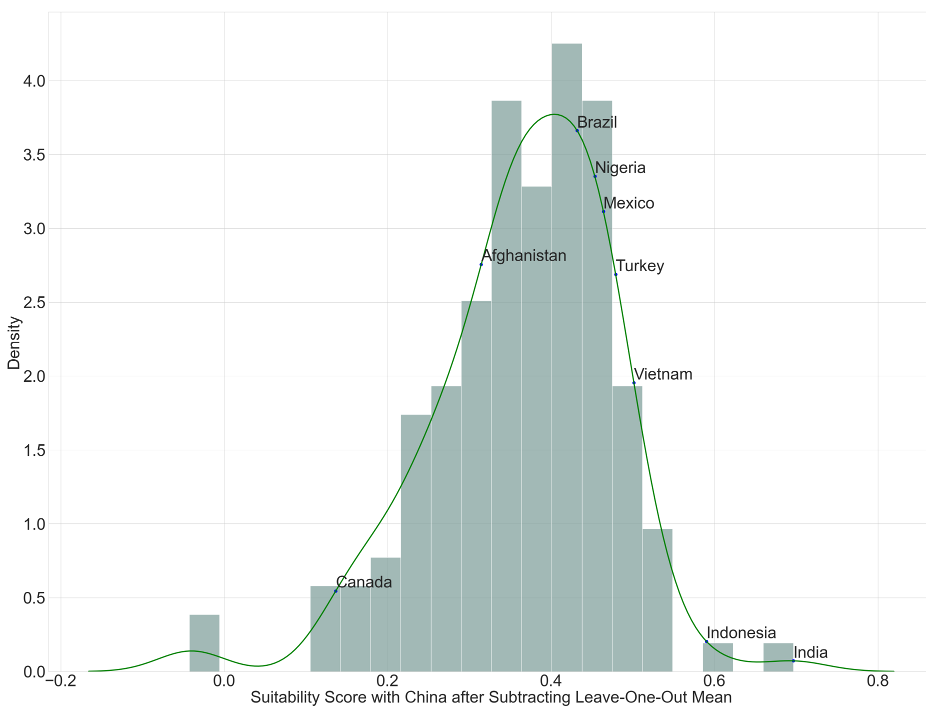
Notes: Figure A.5a displays the log of the total number of deals in China-led and US-led sectors in both China and the US, over time. Figure A.5a the total number of deals in China-led and US-led sectors in both China and the US, relative to the total number of deals in 2005, over time.

Figure A.6: Within-Country, Sector-Level Variation in Business Suitability

(a) AgTech

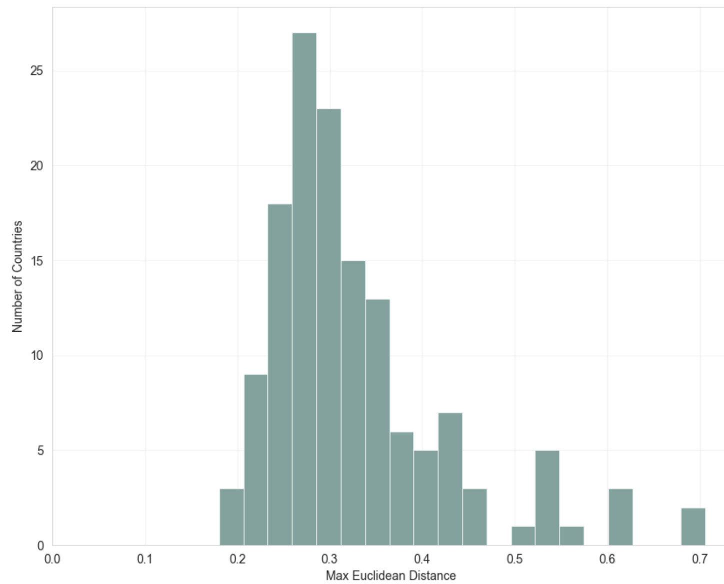


(b) FinTech



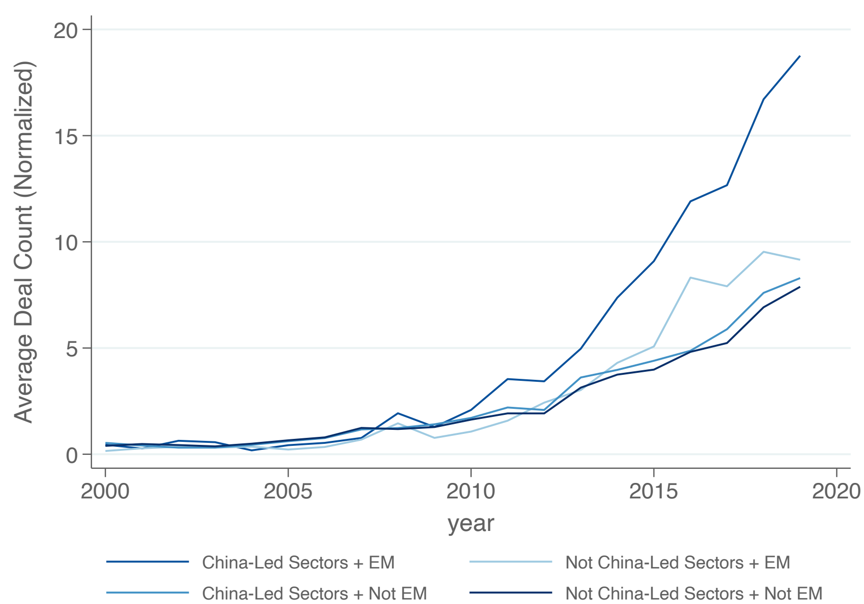
Notes: Figure A.6a displays a histogram of all countries' China-suitability in the AgTech macro-sector, after subtracting average China suitability across all other macro-sectors. Figure A.6b displays the same for FinTech.

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



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

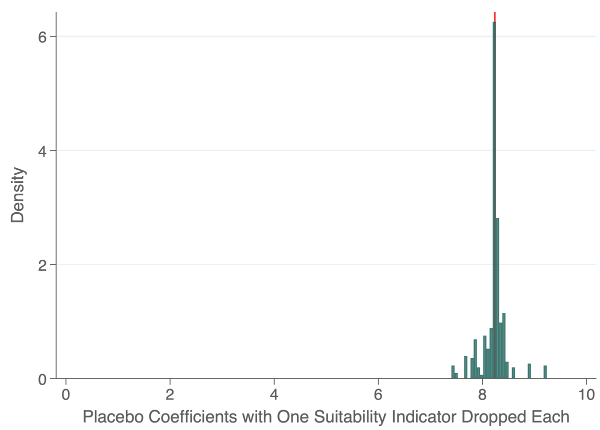
Figure A.8: Raw Trends in Venture Investment



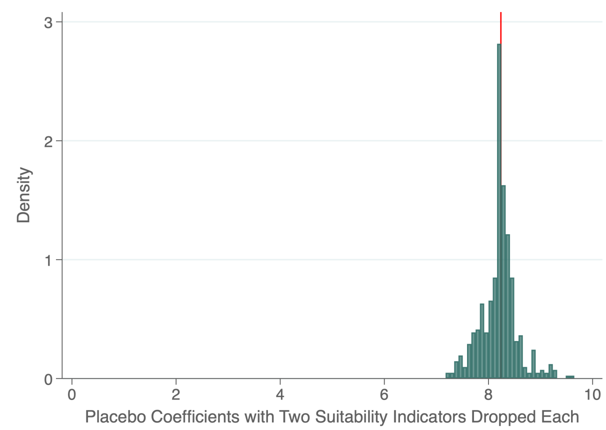
Notes: This figure shows the trend of normalized deals for global markets. The number of deals is normalized by the average amount of deals in the pre-period. Trends are reported separately for China-led and non-China-led sectors, and for deals in emerging and developed markets.

Figure A.9: Robustness to Excluding Indicators from Suitability Measure

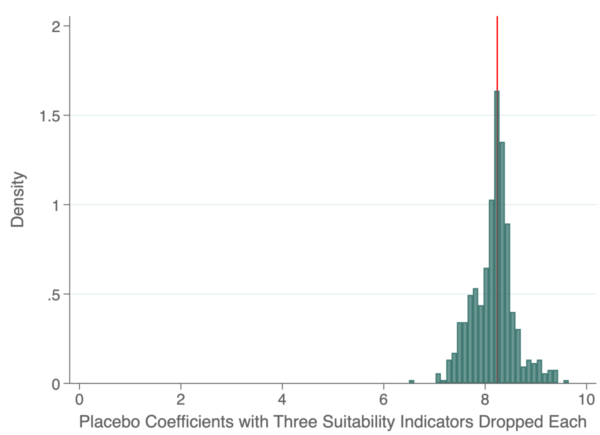
(a) Dropping 1 Indicator



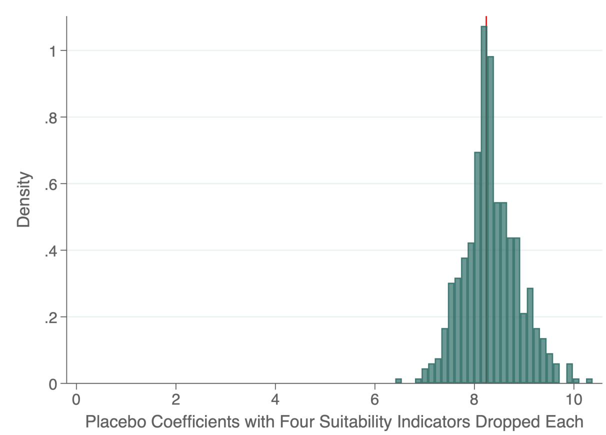
(b) Dropping 2 Indicators



(c) Dropping 3 Indicators

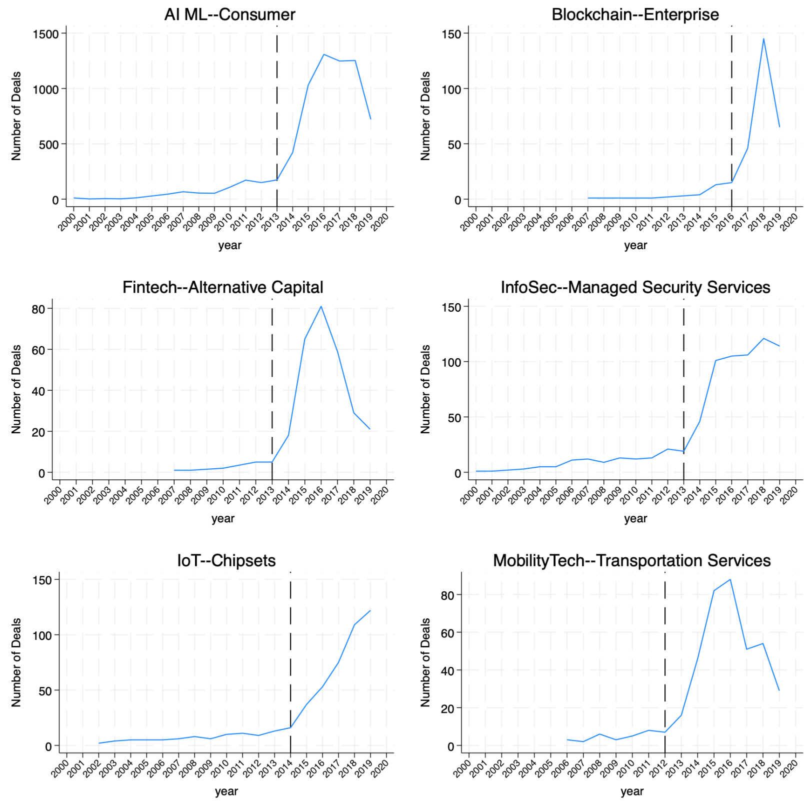


(d) Dropping 4 Indicators



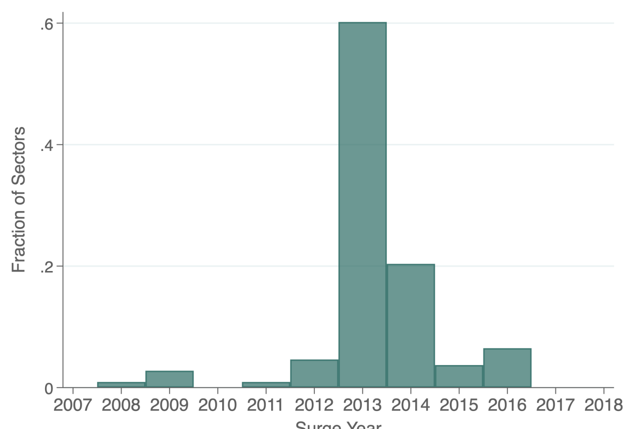
Notes: This figure reports histograms of coefficient estimates from a series of estimates of Equation 2, in which $ChinaSuitability_{cs}$ is replaced with an alternate suitability measure where one, two, three, or four of the indicators used in the suitability calculation are dropped, repeated with 500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

Figure A.10: Examples of Sector-Level Surge Years



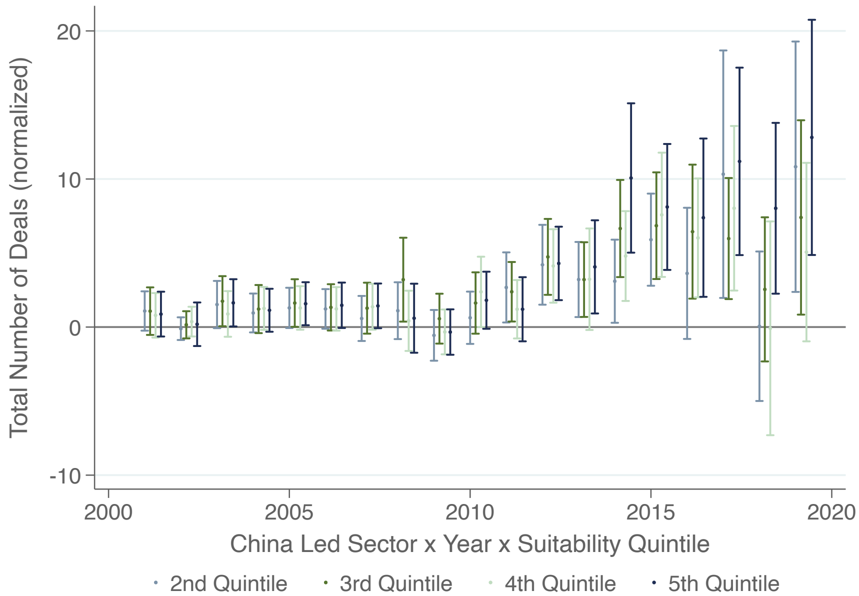
Notes: This figure shows six examples of sector-specific surge years. "Surge year" is defined as the start year of a two-year window in which the number of VC-backed deals received by Chinese companies has the highest growth rate. We restrict attention to two-year windows with at least 10 deals (or 40 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.11: Distribution of Surge Years Across Sectors



Notes: 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."

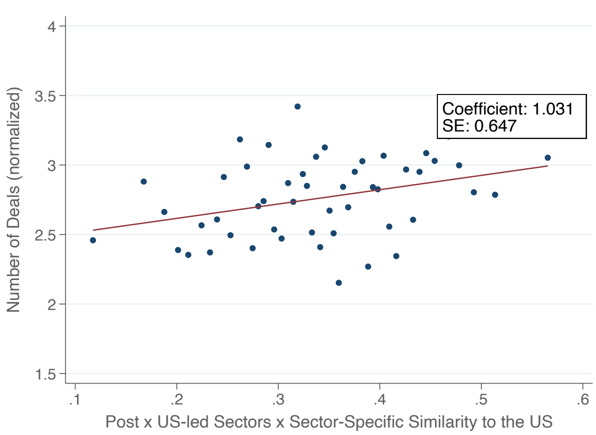
Figure A.12: Suitability and Venture Activity: Dynamics



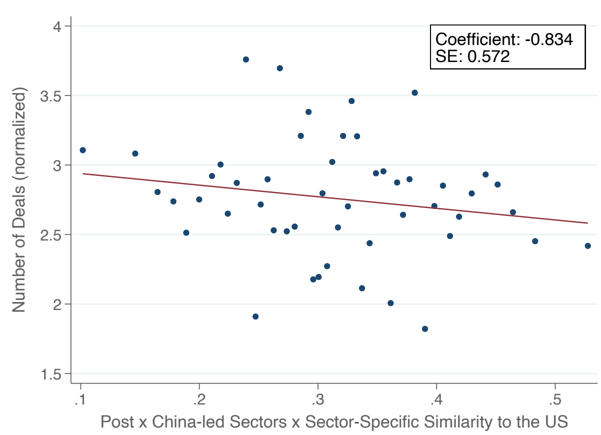
Notes: This figure shows estimates of year indicators interacted with $ChinaLed_s * SuitabilityQuintile^q_{cs}$ where $SuitabilityQuintile^q_{cs}$ is an indicator that equals one if the suitability score is in quintile q. We include estimates of the effect of quintiles two through five, where the bottom quintile is the excluded category, and all coefficients are estimated from the same regression. Standard errors are clustered by country and 90% confidence intervals are reported.

Figure A.13: US Suitability After China's Rise

(a) Post × US-Led × US Suitability



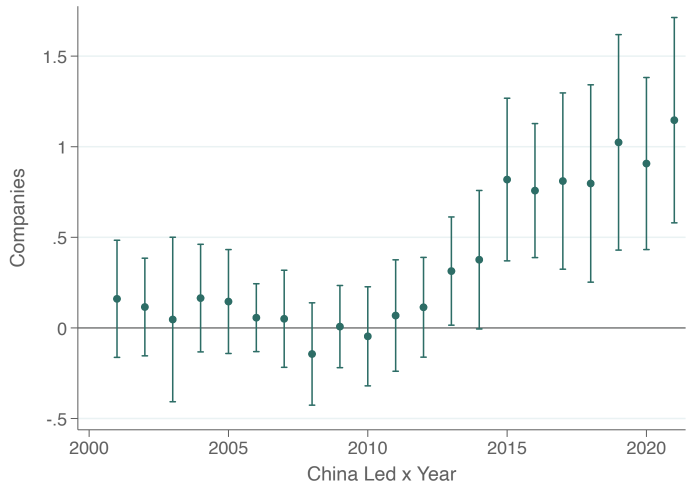
(b) Post × China-Led × US Suitability



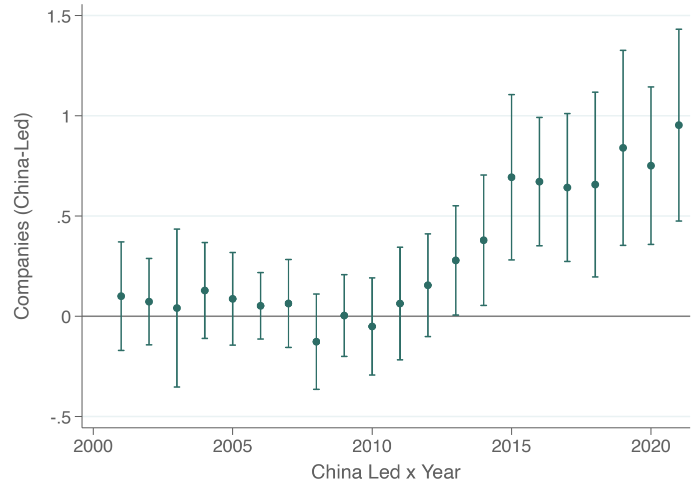
Notes: Figures A.13a displays the relationship between normalized deals and $Post_t \times USLed_s \times USSuitability_{cs}$ and A.13b displays the relationship between normalized deals and $Post_t \times ChinaLed_s \times USSuitability_{cs}$. Standard errors are clustered at the country level.

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

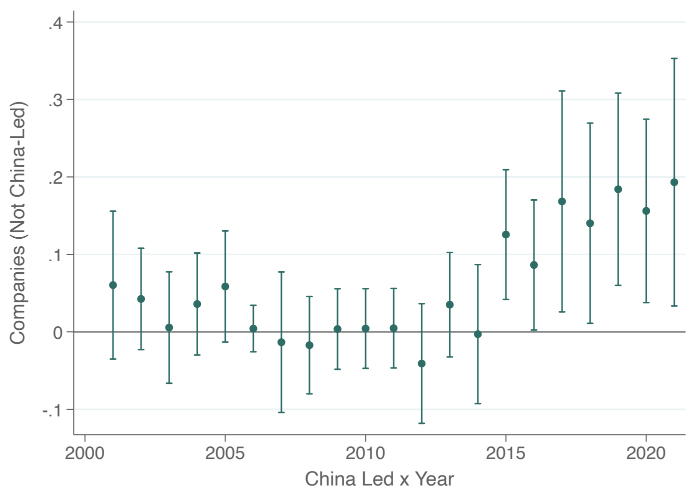
(a) Companies (All)



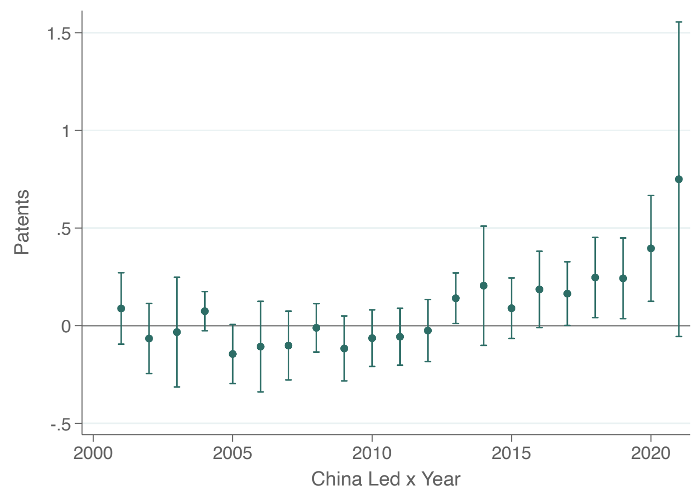
(b) Companies (China-led Sectors)



(c) Companies (Not China-led Sectors)



(d) Patents



Notes: 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%

Notes: 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 figure 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

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

Table A.3: Rise of China Increases Emerging Market Entrepreneurship

	Dependent Variable: Number of Deals (Normalized)				
	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) EM Only	(5) Non-EM Only
China-Led Sector × Post × EM	4.454***	15.901***			
	(0.847)	(3.685)			
China-Led Sector × Post			3.897***	4.796***	0.342
			(0.667)	(0.807)	(0.250)
Sector × Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	No	No	No
Weighting	None	# Deals	None	None	None
Number of Obs	599640	590520	599640	478660	120980
Mean of Dep. Var	3.582	13.299	3.582	3.853	2.508
SD of Dep. Var	45.814	93.076	45.814	51.015	10.251

Notes: The unit of observation is a country-sector-year. EM countries are defined as countries not included in the OECD as of 1980. The dependent variable is normalized by dividing the number of deals in the country-sector-year by the total number of pre-period deals in the country. In column 2, the regression is weighted by the total, global number of deals in the sector during the pre-period. 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 × China Suitability	8.030***	7.408**	7.620**	7.504**	8.025***
	(2.919)	(2.921)	(2.921)	(3.084)	(2.989)
China-Led Sector × Post × China Suitability × GDP pc above China (Pre)	-0.925				
	(1.421)				
China-Led Sector × Post × China Suitability × GDP pc (Pre)		-0.518			
		(0.421)			
China-Led Sector × Post × China Suitability × GDP pc (Post)			-0.457		
			(0.421)		
China-Led Sector × Post × China Suitability × GDP pc (Below China and above 50%)				1.411	
				(1.931)	
China-Led Sector × Post × China Suitability × 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

Notes: 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 below 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: Suitability and Entrepreneurship: Robustness for 2000-2021 Sample

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	9.499**	11.954**	0.113**	0.236**	0.307**
	(3.723)	(4.742)	(0.048)	(0.100)	(0.127)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	12.292***	16.421***	0.144***	0.336***	0.558***
	(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
Suitability × 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	1.018
SD of Dep. Var	57.020	67.300	0.555	0.906	1.540

Notes: 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.6: Suitability and Entrepreneurship: Robustness for *Relative to the World* Measure

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
China-Led Sector × Post × China Suitability	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
Suitability × 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

Notes: 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.7: Suitability and Entrepreneurship: Non-VC Deals

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	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 × China Suitability	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
Suitability × 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

Notes: 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. 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.8: Suitability and Entrepreneurship: "Partial-Freedom" Indicator Assignment

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	8.325***	10.813***	0.086**	0.170**	0.264**
	(2.865)	(3.715)	(0.042)	(0.083)	(0.105)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	11.005***	14.857***	0.122***	0.253***	0.456***
	(3.272)	(4.458)	(0.031)	(0.081)	(0.114)
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
Suitability × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
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

Notes: 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. The suitability measure used in all specifications uses the assignment of indicators to macro-sectors in which coders were given only "partial freedom" to exclude indicators. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.9: Suitability and Entrepreneurship: "No-Freedom" Indicator Assignment

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	10.350**	13.406**	0.140***	0.306**	0.507*
	(5.123)	(6.583)	(0.052)	(0.122)	(0.260)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	15.706**	21.732**	0.133***	0.340***	0.993***
	(6.263)	(8.539)	(0.050)	(0.129)	(0.372)
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
Suitability × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
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

Notes: 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. The suitability measure used in all specifications uses the assignment of indicators to macro-sectors in which coders were given "no freedom" to exclude indicators. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.10: Suitability and Entrepreneurship: Robustness to Dropping Countries with >20% Missing

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	9.402***	11.896***	0.128***	0.249***	0.275*
	(3.154)	(4.082)	(0.043)	(0.085)	(0.154)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	12.261***	15.930***	0.145***	0.302***	0.455**
	(3.670)	(4.957)	(0.029)	(0.081)	(0.176)
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
Suitability × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
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

Notes: The unit of observation is a country-sector-year. Countries for which more than 20% of indicators were missing in all years 2003-2013 were excluded from the sample. 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.11: Suitability and Entrepreneurship: Robustness to Dropping Countries with > 30% Missing

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	8.285***	10.508***	0.108**	0.210**	0.280**
	(2.930)	(3.811)	(0.044)	(0.086)	(0.138)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	10.882***	14.240***	0.132***	0.278***	0.474***
	(3.309)	(4.516)	(0.031)	(0.082)	(0.157)
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
Suitability × 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

Notes: The unit of observation is a country-sector-year. Countries for which more than 30% of indicators were missing in all years 2003-2013 were excluded from the sample. 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.12: Suitability and Entrepreneurship: Robustness to Dropping Indicators with >15% Missing

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	8.573***	10.905***	0.104**	0.202**	0.299**
	(2.954)	(3.826)	(0.044)	(0.086)	(0.121)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	11.052***	14.538***	0.130***	0.269***	0.496***
	(3.318)	(4.520)	(0.030)	(0.082)	(0.139)
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
Suitability × 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

Notes: The unit of observation is a country-sector-year. Indicators for which more than 15% of countries were missing in all years 2003-2013 were excluded from the sample. 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.13: Suitability and Entrepreneurship: Robustness to Dropping Indicators with >25% Missing

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	8.040**	10.063**	0.112**	0.213**	0.283*
	(3.121)	(4.066)	(0.044)	(0.088)	(0.146)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	10.938***	14.177***	0.138***	0.285***	0.491***
	(3.569)	(4.821)	(0.030)	(0.083)	(0.165)
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
Suitability × 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

Notes: The unit of observation is a country-sector-year. Indicators for which more than 25% of countries were missing in all years 2003-2013 were excluded from the sample. 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.14: Suitability and Entrepreneurship: Sector-Specific Surge Year

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Sector-Specific Post × China Suitability	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 × China Suitability	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
Suitability × 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

Notes: 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. The outcome variable and parameterization changes across specifications and is noted at the top of each column. 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.15: Exogenous Shocks to Chinese Leadership: Exploiting Early Unicorns

	China-Led Sector (0/1)		Total Deals (Normalized)			
	(1)	(2)	(3)	(4)	(5)	(6)
Large deals (50m) in China in sector by 2008	0.161^{***}					
	(0.028)					
Large deals (100m) in China in sector by 2008		0.429^{***}				
		(0.070)				
Large/early (50m) deals × Post × EM			3.875^{***}			
			(1.350)			
Large/early deals (100m) × Post × EM				4.038^{**}		
				(1.578)		
Large/early (50m) deals × Post × China Suitability					13.964^{***}	
					(4.120)	
Large/early (100m) deals × Post × China Suitability						10.268^{**}
						(4.048)
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	263	263	599640	599640	552300	552300
Mean of Dep. Var	0.490	0.490	3.582	3.582	3.588	3.588
SD of Dep. Var	0.501	0.501	45.814	45.814	44.979	44.979

Notes: In columns 1-2, the unit of observation is a sector, and in columns 3-6, the unit of observation is a country-sector-year. All deal size information is in nominal U.S. dollars. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.16: Top Countries for Suitability-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%

Notes: 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.17: Results After Controlling for Political Alignment

	Dependent Variable: Normalized Number of Deals			
	(1)	(2)	(3)	(4)
China-Led Sector × Post × China Suitability	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

Notes: 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.18: Serial Investors

	Number of Serial Investors				Serial Investor Indicator			
	(1) All	(2) Only CL Sectors	(3) Any non-CL Sectors	(4) Only non-CL Sectors	(5) All	(6) Only CL Sectors	(7) Any non-CL Sectors	(8) Only non-CL Sectors
China-Led × Post	0.109	0.052	0.056	0.028**	0.012	0.008	0.017*	0.014***
× China Suitability	(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

Notes: 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.19: 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

Notes: 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.

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.