Appropriate Entrepreneurship? The Rise of Chinese Venture Capital and the Developing World

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Abstract

Global high-potential entrepreneurship was traditionally dominated by rich countries, especially the US, until the rise of China as a venture capital powerhouse. We explore the international ramifications of China's rise, using comprehensive data on global venture activities. We document three sets of findings. First, as the Chinese venture industry rose in importance, investment increased substantially in other emerging markets, particularly in sectors dominated by Chinese companies. Using a broad set of country-level economic and social indicators, we show that this effect was driven by country-sector pairs most similar to their counterparts in China. Second, turning to mechanisms, we show that the increase in venture investments in emerging economies was spurred by local investors and new firms whose business models more closely resembled those of their Chinese counterparts. The findings are not driven by Chinese investors, by countries politically connected to China, or by sectors prioritized by the Chinese government. Third, we find that this growth in emerging-market investment had positive spillovers on sectors in which China was not a global leader and had positive city-level effects on both business formation and patenting. Taken together, our findings suggest that developing countries benefited from the rise of Chinese entrepreneurship, especially where Chinese businesses and technologies were most "appropriate" for local economic conditions.

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1 Introduction

Global investment in innovation and entrepreneurship has traditionally been concentrated in high-income countries. A growing body of evidence suggests that such concentration has led to the development of technologies that are suited to rich countries but often inappropriate and unproductive in low-income parts of the world. For example, innovators may prioritize the development of capital- or skill-intensive technologies that are less productive in developing contexts, where capital and skilled labor are scarce.[1] As a result, the growth of innovative investment in a low-income country may have major consequences beyond its borders, by generating technologies that are appropriate for the broader developing world.

We examine this hypothesis, focusing on venture capital (VC) investment. VC — responsible for $340 billion (in current dollars) of investment worldwide in 2021 — is critically important for the development of innovation, employment, and economic activity more generally.[2] While VC investment was heavily concentrated in the US for much of its history, the last decade has witnessed a dramatic rise of Chinese venture activity, unparalleled by any other developing country or any other form of research or technology investment. In 2001, the US represented the location of 88% of global venture dollars invested, and other developed countries the majority of the remainder (7%).[3] By 2019, global venture activities became bipolar: while the US continued to lead with 42% of global investment, China had surged to account for 38% of the total (65% of the non-US portion). Thus, this episode presents a singular opportunity to understand the global consequences of a developing country rising to global entrepreneurial leadership.

In this paper, we investigate the international ramifications of China's emergence as a VC powerhouse. Does VC investment in other emerging markets increase in sectors where China leads in investment? Is this driven by the fact that businesses developed in China are more *suitable* for the characteristics of those countries? And, if so, what are the broader economic consequences of these new investments in developing countries?

One of the defining characteristics 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 them-

[1] This is described in Basu and Weil (1998) and Acemoglu and Zilibotti (2001). Also see Moscona and Sastry (2023) on how innovation in agriculture is designed for the ecological conditions of high-income countries and Kremer (2002) and Kremer and Glennerster (2004) for similar patterns in biomedical research.

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

[3] Throughout the paper, we define developed market countries as the original members of the Organization of Economic Cooperation and Development, and those that joined through 1980.

selves, as seen by self-described ventures ranging from the "Amazon of Indonesia" to the "Zappos of Europe."[4] This approach of investors can be understood as a natural response to the intensive uncertainty and informational asymmetries that surround early-stage companies (Gompers and Lerner, 1999).[5] But reliance on past successes in venture decision-making may have a dark side as well: a misallocation of capital and talent. 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. Such misalignment may be especially strong between the US and developing countries.

The dramatic rise of China's VC sector over the past decade has the potential to reshape these dynamics. Anecdotally, Chinese firms have been increasingly emulated by startups around the globe. For example, while startups geared toward online elementary and secondary education never took off in the US, perhaps because of better access to brick-and-mortar education, there was a dramatic surge in Chinese investment in 2010s. This growth was followed by an emerging market boom, most notably in India; Byju's, valued in 2022 at $22 billion with over 150 million registered students, is the most famous example. Investors in these Indian startups, many of which were local venture funds, consciously emulated Chinese business models: Akhil Shahani, the Managing Director of the 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 and may justify the high valuations that companies in this sector command."[6]

While this example suggests that China's rise could benefit other emerging economies by developing more appropriate technologies, there are also several reasons why this may not be true in general. Investors may not have systematically departed from their historic reliance on US benchmark companies. Even if they have, China's economy may be sufficiently different from other emerging economies, or beholden to political pressures, that businesses developed there are not broadly applicable. Finally, it is possible that the best business ideas are not specific to any particular context, implying that the specific countries that serve as global VC leaders do not meaningfully impact global patterns of

[4]Masayoshi Son, the founder of Softbank (undoubtedly the largest global venture investor over the past three decades), makes this explicit in his "time machine theory," which posits that countries such as India wait for the industry development in the more advanced economies (in particular, the US) like sitting in a time machine. Source: `https://shorturl.at/ftFIP`.

[5]This may be particularly true in settings where the rule of law is less well established and hence where investors and entrepreneurs are unable to fully address these concerns through contracts (Kaplan and Strömberg, 2003; Lerner and Schoar, 2005).

[6]Source: `https://inc42.com/features/the-past-present-and-future-of-edtech-startups/`. In Section 2.3, we describe additional examples of this pattern.

entrepreneurial success. Thus, in order to determine the global consequences of emerging market entrepreneurial leadership, it is essential to turn to the empirical analysis.

To investigate the international ramifications of China's VC emergence, we combine several data sources and new empirical measures. First, we compile comprehensive records on venture deals around the world between 2000 and 2021 using PitchBook, a venture capital database designed from its inception to have global coverage. The database includes information about each financing round — including the size and capital providers — as well as a description of each company.[7] In total, we compile data on 179,899 venture deals involving 94,169 firms in 155 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. There is substantial heterogeneity in Chinese growth across sectors, and we define sectors with above-median Chinese participation (relative to the US) as "China-led" sectors. These 266 sectors are categorized by PitchBook into fifteen "macro-sectors" (e.g., EdTech, AgTech, FinTech), which we also make use of to investigate broader differences across countries.

Third, we seek to measure the potential economic "suitability" of Chinese entrepreneurship in all country-sector pairs. To do so, we compile data on a large array of country-level social and economic conditions 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 finally, 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 is higher in developed countries. However, there is also substantial variation in similarity to China across sectors in each country. This variation is a critical component of 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

[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.

[8]This "triple-difference" specification includes all two-way fixed effects, making it possible to fully ab-

is a first indication that the rise of China spurred new venture activity and business ideas 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 suitable. 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. Our baseline estimate suggests that a one standard deviation increase in macro-sectoral 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 65%. Together, these findings indicate that the rise of VC in China increased global entrepreneurship, driven by emerging market sectors where Chinese technology and business ideas would be most suited to the local context.

The results are robust to a range of sensitivity checks, including alternative sample definitions and strategies for constructing the suitability measure. The findings are also qualitatively similar using a range of different outcome variables, including total investment value, total value *per deal*, and a range of parameterizations of the baseline dependent variable. The findings are also similar if we exploit early and largely idiosyncratic Chinese startup successes as predictors of Chinese sector-level growth. Finally, we present a series of falsification tests that are all consistent with our identifying assumptions and a causal interpretation of our estimates. We re-estimate our regression specification using a series of placebo versions of the key independent variable: *(i)* instead of using country-by-sector similarity with China, we use similarity with *all other countries*; *(ii)* instead of the actual country-by-sector similarity score with China, we use that of a *randomly selected sector in the same country*; and *(iii)* instead of the actual sector-specific year in which China's VC began to take off, we use a *randomly selected year* for each sector to define the post-period. In each, our baseline estimate is larger than *all* placebo estimates.

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

sorb 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). Moreover, we do not observe any pre-existing trends in investment in these sectors prior to China's rise.

ity between descriptions of new firms and descriptions of Chinese firms founded in the same sector during the preceding five years. Again, this effect is restricted to country-sector pairs with high suitability of Chinese technology. 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 document that the increase in venture investments in emerging economies is driven by local investors. While US-based and Chinese venture funds also contributed, by far the largest increase in investment is observed for local funds.[9] Finally, we 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. These findings suggest that part of the increase in venture activity was driven by investors' greater willingness to fund existing companies in emerging markets, provided that they were in country-sector pairs where a successful model had already been developed in China. The rise of Chinese VC not only led to the development of new business ideas, but also helped validate existing ideas that could then more easily attract investment elsewhere in the world.

Intriguingly, we find little evidence that the international diffusion of Chinese business models is shaped by explicit political factors. We measure each country's political allegiance with China using data on United Nations (UN) voting patterns and regime characteristics. We similarly assess each sector's importance to the Chinese government by compiling published lists of strategically relevant sectors and linking them to the sectors in our data. We find no evidence that political links between countries drive our baseline results: the baseline estimates are similar after restricting the sample to China's "friends" or "enemies" and after excluding the politically important sectors from the analysis. Interestingly, the results are substantially weaker after restricting attention to the politically important 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, show that the results are not driven by failed companies. Instead, there are large positive effects on companies that are acquired or go public, as well as firms where is not yet any exit. Thus, our estimates are not driven by failures or short-run fads. We then document the presence of cross-sector spillover effects. Greater venture investments in China-led sectors were accompanied by the emergence of serial entrepreneurs — indi-

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

viduals who found multiple startups.[10] Importantly, we find that these serial founders are disproportionately likely to start subsequent companies in sectors that are *not* China-led. That is, the rise of investment in China-led sectors led to serial entrepreneurs who broadened their focus and developed businesses without the need for a Chinese benchmark for venture fundraising. We find a similar pattern for local serial investors. Last, we document the presence of geographic spillovers. Localities with a greater pre-existing share of firms in China-led sectors experienced an increase in the number of new firms established locally after the rise of Chinese VC. These effects are driven by *both* companies that are in sectors led by China and companies that are not. We also document positive city-level effects on patenting activity, indicating that the rise of China had broader positive effects on innovation. These patterns are especially strong for cities in developing countries, consistent with all previous evidence that the rise of China boosted local entrepreneurial ecosystems in emerging economies.

Taken together, our findings suggest that the approach to venture investment based on following US benchmarks might have limited VC growth in developing countries. Companies designed for the US market may not have been suitable in developing countries and *vice versa*. If the rise of Chinese ventures substantially increased the "appropriateness" of capital allocation and entrepreneurial activity in emerging economies—because businesses designed for China are more suited for much of the world than businesses designed for the US—it may have strong implications for growth. More broadly, these findings suggest that new emerging market centers of R&D, in China or elsewhere, could have large and global productivity impacts. We discuss these more speculative consequences of our findings, including the implications for "soft power" and the consequences of China's very recent shifts in venture policy, in the conclusion.

This work builds on three strands of existing literature. First, there is a substantial 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 may shape technology diffusion and productivity differences across countries (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006; Moscona and Sastry, 2023). While existing work in this area has highlighted the costs for developing countries of the concentration of R&D, we investigate the benefits of expanding R&D to new markets. We also extend this set of ideas about technology diffusion to the study of entrepreneurship.

[10] Prior work suggests these founders are particularly important for the growth of local centers of entrepreneurship (see, e.g., Gompers et al., 2010; Mallaby, 2022).

Moreover, much of the technology diffusion literature (e.g., Keller, 2002; Comin and Hobijn, 2010) says relatively little about the mechanisms behind such diffusion. Inasmuch as the literature has investigated mechanisms, much existing work 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, as we show here.[11]

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 the growth of Chinese innovation in recent decades and document that it has affected patterns of entrepreneurial activity far beyond China's borders.

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, and R&D investment in developing countries.

This paper is organized as follows. The next section describes the recent history of VC and in particular, its rise in China and expansion to emerging markets. Section 3 describes our data and measurement. Section 4 presents our main results and Section 5 presents our evidence on mechanisms. Section 6 investigates the broader economic implications of China-led VC growth. 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 venture investment was the emergence of China in the 2010s. 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

[11] More generally, very little has focused on knowledge flows from startups. One exception is Akcigit et al. (2023), which focuses on knowledge flows to corporate investors in US startups.

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 the global venture investment, amounting to on average US$ 63.04 billion in annual investments. These totals represented a 501% and 2,060% increase compared to the 2013 share and level.

It may be wondered to what extent these Chinese ventures represented true innovations, as opposed to 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 manufacturing of electric vehicle batteries.

The recent rise of Chinese venture investment and entrepreneurship, in part, reflects a broader rise in Chinese innovation. Appendix Figure A.1 illustrates the share of global R&D investment, as well as the share of global scientific publications of China. While the share of innovation happening in China has increased using both measures, the pattern is much 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.

2.2 Unprecedented emerging market investment

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 rising R&D investment outside of high-income parts of the world. 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 economies and recently developed countries in the year that they reached about the same level of GDP per capita. The comparison is presented in Table 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 markets or recently developed nations represented more than 1% of the global venture investment when they reached this level of GDP per capita. For instance, Mexico's GDP per capita climbed to US$ 12,613 in 2000, but only 0.28% of the venture capital in the world was invested in Mexican firms. A similar pattern is also observed among other dimensions of innovation, such as the share of world's scientific publications, R&D expenditure, and filed patents, but China's rise to global leadership is far more 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, such upward sloping curve is substantially shifted to the left for China.[12]

Venture investment is also playing 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 systematically document the importance of venture capital in emerging markets, we follow Lerner and Nanda (2020)'s methodology for the US. We identify the share of young, publicly traded firms headquartered in each country that are venture 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 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 a more detailed discussion).

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. In other words, venture investments have become a non-trivial component of firm growth in emerging markets. While venture capital's contribution to publicly listed firms in emerging markets is catch-

[12]It is interesting to note that while India's GDP per capita is still less than half of that in China, it already captures more than 5% of the world's venture investment. 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.

ing up to that in China and other developed markets, it remains substantially lower than that in the US. This could reflect many factors, including the maturity of domestic financial markets in many emerging economies. It could also be a result of the fact that the venture investors in these markets lack appropriate and successful benchmarks, a mechanism that we investigate explicitly in this paper.

2.3 Venture investment and industry benchmarks

Our empirical approach is grounded in the observation that venture capitalists invest in settings characterized by substantial information problems. 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.

As a result, venture investors frequently look for indications that new ventures correspond in important ways to ones that have proven successful in the past. Among the indicators may be entrepreneurial characteristics — Y Combinator's founder Paul Graham's waggish observation that he "can be tricked by anyone who looks like Mark Zuckerberg" is illustrative—but also more generally similarities in business models.[13] In the emerging market context, many firms have sought to emulate successful concepts such as e-commerce, mobile payments, and buy now/pay later.[14]

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 discuss in the introduction, Appendix Figure A.3a plots the timing and amount of venture investment received by startups in this sector around the world. One observes 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

[13]For the Paul Graham quote, see `https://www.nytimes.com/2015/07/02/upshot/the-next-mark-zuckerberg-is-not-who-you-might-think.html`. Venture blogs make this point numerous times. Illustrative examples are `https://www.av.vc/blog/best-practices-in-pattern-recognition`, `https://alumniventuresgroup.medium.com/the-importance-of-pattern-recognition-in-venture-capital-e178a6b38714`, and `https://www.digitalnewsasia.com/insights/two-most-important-words-venture-capital-pattern-recognition`.

[14]For instance, in ridesharing, 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.

could be emulated in emerging markets. Between 2017 and 2021, there was a 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.

While this is just one example, writing by practitioners suggests that it may represent a broader phenomenon. Companies in emerging economies may systematically look to China for inspiration since Chinese companies have had to grapple with similar characteristics and conditions. One other example is the rise of 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 — in many emerging economies after its origination in China.[15] Similarly, the formation of the Indonesian last-mile delivery unicorn, J&T Express, was motivated by the experience of its co-founder, Jet Li, while serving as a country manager for a major Chinese electronics firm.[16]

Christopher Schroeder, a venture investor focused on the Middle East, summarizes this pattern; he writes, "For all the obvious cultural and geographic differences, [companies in China and other emerging markets] have navigated challenges not contemplated in the West—navigating particularly hard last mile logistics, dealing with rapidly changing regulatory regimes, educating millions of consumers to use fintech 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]

Thus, there are several examples of Chinese companies solving problems or meeting consumer demands that are common across emerging markets. Anecdotally, this has facilitated entrepreneurship in developing countries around the world. Entrepreneurs learn from business ideas first developed in China but that are applicable to their local context as well. Meanwhile, investors are willing to invest in new companies that can

[15]Source: https://www.sturgeoncapital.com/wp-content/uploads/2022/07/Sturgeon-Insights-Social-Commerce.pdf,https://labsnews.com/en/articles/business/social-commerce-platform-favo-empowers-a-entrepreneurial-partners-network-in-brazil-and-peru/?fbclid=IwAR098WzRyGeUhEC7GwwxzQ19dW6Kshw4I2tDFUL2bHKC76QBC5Wnak9DVpE

[16]Source: https://asia.nikkei.com/Business/36Kr-KrASIA/Boom-or-bust-The-story-of-J-T-Express-in-China;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.

[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.

point to one of the growing number of Chinese success stories as a benchmark, even if the business has not been (or would never have been) successful in the US.

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.[18] 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. While coverage before 2000 is spotty, they made considerable efforts to backfill earlier years in the 2000s. The information in the PitchBook database is gathered from contacts with funds and portfolio firms, news stories, and regulatory filings.

We aim to compile comprehensive venture investment deals around the world between 2000 and 2019.[19] In particular, we extracted 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. We validated that the (excluded) growth equity category does not have significant numbers of later-stage VC deals.

In Table 2, Panel A, we present a series of summary statistics. The compiled data covers 94,169 companies from 155 countries that received 179,899 venture deals in total. On average, companies in the US receive 2.22 venture investments during their life cycles, as compared to 1.89 for companies in China, and 1.54 for companies in other emerging markets. The average amount for each deal is US$ 13.55 million. Approximately 44.12% 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 constitute a venture capital (as opposed to a later-stage) transaction.[20] To validate the

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

[19]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.3).

[20]In our conversations with practitioners, many felt that PitchBook was the best database for the purposes

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 validation exercise in greater detail, along with other evidence of validation.

3.2 Categorizing firms into sectors

To examine the impact of China's emergence on venture investment in other emerging markets, we take each country's annual investment activities in a specific sector as the primary unit of analysis. This requires us to categorize all venture-relevant firms into as detailed an industry classification scheme as possible. To do so, we used 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 trained a BERT model 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.[21] We then use these data to assign the universe of companies to these sector categories. In total, we are able to assign 402,695 companies, or approximately 91.09% of the companies tracked by PitchBook, into a total of 266 sectors. 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. As a result, 88,267

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.

[21] 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.

companies, or approximately 93.73% of the companies that have venture capital deals tracked by PitchBook, are classified into 266 sectors. 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 2, Panel B.1, provides summary statistics of the sector-level data. On average, each sector has 1021 firms. Categorization into each sector is treated as a binary and independent task; thus, companies may be assigned to multiple sectors. About 17.36% of the firms are categorized into just one sector, 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. 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. While in some sectors there are zero or a very small number of deals that take place in China, for a large number of sectors a greater number of deals take place in China compared to the US. One such sector is "solutions for students (primary and secondary)," which we described in Section 2 and is marked in red in Figure 2. The sectors corresponding to social commerce platforms and last mile delivery, also described in Section 2, are labeled as well.

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 a sector to be "China-led" if 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.

This choice to define Chinese sector-level leadership based on its share of venture activity compared to the US (and not the rest of the world) is motivated by two features of VC investment. First, it is motivated by the bipolarity of the global venture industry in this period. Outside of the US and China, no single country represented a substantial share of global investment.[22] Second, it is motivated by the large amount of case study

[22]The distribution of funding can be illustrated by calculating the ratio of annual venture investments

evidence, some of which is described in Section 2, suggesting that the vast majority of 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 benchmark companies. Nevertheless, we show in Section 4.2 that all results are very similar if we instead define China's sector-level leadership based on its share of global deals.

Table 2, 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.[23] For this part of the analysis, we focus on 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

(in dollars) in the nation with the greatest activity aside from the US and China (where investment reached 91% of US levels in 2019) relative to that in the US. This follow-on country, typically the United Kingdom or India, averaged only 6.9% of the US level of VC deployment in the years between 2001 and 2021.

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

and crop production are most relevant to Agriculture Tech and Food Tech.

Members of our team assigned indicators to macro-sectors using three complementary methods, with different levels of coder freedom.[24] In a first method (our baseline), coders were fully free 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. 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.[25] 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—on account of the fact that it is constructed using a broad set of country-level indicators—and across macro-sectors within countries—on account of the fact that only certain indicators are 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

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

[25] Appendix Table A.1 gives more examples of the indicators chosen for specific macro-sectors.

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 from the US to 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.5 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 4 displays histograms of China-suitability for AgTech (4a) and FinTech (4b), 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 4 documents that it has far higher potential suitability in FinTech compared to AgTech. The same is true for Nigeria and Indonesia. Afghanistan, on the other hand, has far higher potential suitability in AgTech compared to FinTech.

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 our hypothesis is true. 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.[26] 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.[27]

Panel A of Figure 5 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.[28,29]

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

4 Main results

4.1 Empirical strategy

Our goal in this section is to isolate the impact of the rise of Chinese ventures and to assess whether emerging markets emulate Chinese ventures because Chinese entrepreneurship

[26]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`.

[27]Results from a specification with a pooled post period are reported in Appendix Table A.2. 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.

[28]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.

[29]Figure A.6 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).

is appropriate for local socioeconomic conditions. To do this, we introduce the baseline specification of our empirical analyses, where we estimate the differential effects of the rise of Chinese VC in contexts with *ex ante* (sector-specific) socioeconomic conditions are more or less similar to China.

Specifically, we estimate the following regression model:

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

where the *China suitability* 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.[30]

Our hypothesis is that β>0, which would imply that the international growth of China-led sectors took place disproportionately in country-sector pairs where we predict Chinese technology to be most suitable. However, recall from the introduction that there are many reasons why this may not be the case. First, the bulk of venture activity may still follow the US template, either because of its initially dominant position in venture capital or because the idiosyncrasies of the Chinese market may deter others from emulating it. Second, even if emerging economies follow China (as suggested by Figure 5), it may be for reasons (e.g., political ties) that have little to do with the suitability of Chinese technology.

The specification includes three sets of fixed effects that account for several important forces. First, *country* $*$ *year* fixed effects control for trends in nations' entrepreneurial environments, their evolving ties to China, etc. These will capture, for instance, shifts in country-level growth rates, as long as these changes did not disproportionately affect China-led sectors. Second, *sector* $*$ *year* fixed effects control for global trends in entrepreneurship for each sector. Shifts that favor one sector or another will be appropriately controlled for, unless, for instance, these shifts disproportionately affect country-sector pairs with economic characteristics more similar to China. Finally, *country* $*$ *sector* fixed effects control for differences in entrepreneurial specialization by country, as long as these do not sharply change after 2013.

The main empirical concern throughout this part of the analysis is that some sectors grew in emerging markets for reasons *unrelated* to China's investment dominance. For example, the findings presented in Figure 5 may be driven by a common shock or trend, specific to emerging economies, that led to the growth of particular sectors. In the specification outlined by Equation 2, however, this would only be a concern if this emerg-

[30]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.

ing market growth happened to also be restricted to country-sector pairs most similar to China. Moreover, Section 4.3 presents a series of falsification exercises consistent with a causal interpretation of our estimates, and in Section 4.4 we present estimates that exploit exogenous variation in sector-specific take-off in China driven by early and idiosyncratic entrepreneurial success.

4.2 Main estimates

Table 3, 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 trend in the cross-sector distribution of investments between emerging and developing countries. The estimate of β is very similar, suggesting that even within emerging markets, sector-specific similarity to China is a strong predictor of the spread of China-led sectors.

Finally, columns 3-4 of Table 3 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$\times$sector sets with low (column 3) vs. high (column 4) values of the China-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.

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.

Alternative specifications and robustness The baseline results presented above are robust to a range of alternative specifications, presented in Table 4. Column 1 of Panel A first replicates the baseline estimate from Table 3 for reference. Column 2 shows that the estimates are very similar if we weight the regression by the global number of pre-period deals in each sector, in order to make sure that the findings are not driven by smaller or less important sectors. In column 3, we use the (inverse hyperbolic sine transformation of the) number of deals as the dependent variable, rather than the normalized count. Reassuringly, the estimates are qualitatively very similar.

In columns 4 and 5, we turn to estimates of deal size in order to make sure that the findings are not driven by small deals. In column 4, the outcome variable is the (inverse hyperbolic sine transformation of the) total deal value in the country-sector pair. Again, we estimate a positive effect. Finally, in column 5 the outcome is the (log of the) average deal value. We also see a positive effect, suggesting that not only did the number of deals and total investment increase, but so too did the amount invested per deal.

Panel B of Table 4 repeats all estimates from Panel A, except uses the "strict" definition of China-led sectors to construct the independent variable. That is, rather than define China-led sectors as those with above median Chinese investment, we define China-led sectors as those where China has invested more than the US in absolute terms. We estimate positive values of β in all columns, which are often larger than the estimates in Panel A. The larger effects are intuitive, since these estimates restrict attention to the smaller set of sectors in which China is most dominant.

We present additional robustness checks in the Appendix. First, in Appendix Table A.3, we follow the structure of Table 4 except include the years 2020 and 2021 in the sample. In the main analysis, we end our sample in 2019 to avoid complications induced by COVID-19; however, reassuringly, the results are very similar in magnitude if we also include the COVID-19 years.

Second, in Appendix Table A.4 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. Our results are all very similar using this alternative definition, consistent with the fact that global VC is dominated by China and the US and the sectors that we identify as being dominated by China are very similar using both methods.

Third, in Appendix Table A.5, we again 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 if non-VC funding went in the opposite direction. However, we find no evidence of this pattern; estimates in Appendix Table A.5 are all positive and half of the estimates are statistically significant. This suggests that, if anything, the direction of non-VC financing reinforces our baseline findings. This finding dovetails with our results in Section 6 (below), which suggest that the rise in VC investment had positive spillovers on other forms of business formation and innovation.

Finally, to alleviate concerns that our main results are driven by our specific choice of indicators in the construction of our suitability measure, we conduct two sets of exercises.

We first show that the results are very similar using our alternative (and more restrictive) strategies for assigning indicators to macro sectors (see Sections 3.3 and Appendix C). In Appendix Tables A.7 and A.8, we re-produce all baseline estimates using the alternative suitability measures and all estimates are very similar in both magnitude and precision.[31] In the second set of exercises, we address the concern that our findings are driven by a small number of indicators, calling into question our empirical strategy. We re-produce our baseline results after re-constructing the suitability measure after one, two, three, or four indicators are randomly excluded from the suitability measure, and repeat each process 500 times. In Appendix Figure A.7, we report the histograms of coefficients in the main specification when using these 2000 alternative suitability measures. Reassuringly, these estimates are clustered closely around our baseline estimate, marked with a vertical red line.

Timing and dynamics In Figure 6, we report the effects by suitability decile, separately for the pre-period (before 2013) and post-period (after 2013). The first decile is the excluded group and all bars display estimates of the interaction between $ChinaLed_s$ and the appropriate decile indicator. If the main effect is driven by the rise of Chinese entrepreneurship, we would expect no difference between country-sector pairs with different values of the suitability index prior to the rise of China. That is precisely what Figure 6a conveys: the effect of each decile is small in magnitude and statistically indistinguishable from zero. Figure 6b shows, however, that after 2013, there is a clear positive relationship between the decile of the suitability index and venture activity. With two exceptions, the bars increase moving from left to right. Social and economic similarity to China was a strong determinant of the global growth of sectors led by Chinese companies.

Figure 7 explores these dynamics in greater detail. In particular, we include 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 all country-sector pairs increasing relative to the excluded group, but with the highest suitability quintile (dark blue) increasing the

[31] 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. Since we take averages from 2003-2013, an indicator or country is only dropped if the value is missing for *all* years from 2003-2013. However, we show in the Appendix that the results are very similar if we use alternative thresholds. In Appendix Tables A.9 and A.10, we show the results are similar if we instead drop countries with greater than 20% or 30% missing values. And in Appendix Tables A.11 and ,A.12, we show the results are similar if we instead drop indicators with greater than 15% or 25% missing values. These estimates are described in greater detail in Appendix C.

most. The gap widens over the course of the sample period.

As a final strategy to document that the main results capture venture activity that *followed* a surge in venture activity in China, we identify a sector-specific "surge year" for all sectors. To do this, 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.[32] Appendix Figure A.8 shows the number of Chinese deals over time for several example sectors, with the surge year marked by a vertical line. Appendix Figure A.9 shows the distribution of surge years identified, where most sectors are identified to have 2013 as surge year, which is why we use this year in our pooled baseline analysis.[33] We re-estimate Equation 2 replacing $Post_t$ with $Post_{st}$, a sector-specific indicator that equals one starting the year after the surge year for all China-led sectors. Appendix Table A.6 re-produces Table 4 except the regression specification uses the sector-specific post period. If anything, the estimate using the sector-specific timing is larger than our baseline result. Moreover, it is also in the far right tail of the distribution of estimates when we randomize the surge year across China-led sectors (but maintain the same number of sectors assigned to each year). The distribution of these estimates is displayed in Figure 8 as a green histogram and our estimate from this specification is marked with a vertical red line. These estimates show that the rise in venture activity in China-led sectors exactly followed the sector-level timing of growth in China.

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.[34] As detailed in Appendix D, we find that the rise of China increased emerging market venture deals by 65% using our baseline China-led measure and 26% using our strict China-led measure, relative to the counterfactual that the VC investment continued to be dominated by the US. This number is substantial and also likely underestimates the true effect, since our suitability measure

[32]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." 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.

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

[34]This exercise relies on two 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" and in country-sector pairs with zero suitability. This implies that the magnitudes we present are likely underestimates. In fact, 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 necessary assumption is that fixed effect estimates are held constant in the counterfactual without the rise of China.

is an imperfect proxy for the potential diffusion of Chinese technology and business ideas around the world.

A related question is what might have been the impact if a country other than China grew over the past decade in China's place? This is admittedly a fanciful counterfactual, since China's rise to prominence is unique and a defining feature of global venture capital today. Nevertheless, we think it is informative for benchmarking the effect of China *per se* against the potential effect of growth in any other emerging market.

To investigate this question, 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 there would have taken place in each emerging economy if each other country had risen in China's place. 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. In order to incorporate the potential scale of innovation in each country, in a second exercise we also scale the number of sectors "led" by each country by its GDP relative to that of China. We use the strict China-led measure in this exercise for better empirical tractability.

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 34% (as opposed to the 26% increase estimated above using strict China-led measure). Pakistan is followed by Indonesia and Brazil. 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; China is simply the *only* emerging economy (so far) that rose to global VC leadership. 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 — no other country comes close to China. The country in distant second is Japan, which we predict would have increased emerging market venture activity by 9%. In Appendix D, we describe in detail how we conduct this simulation exercise. In Appendix Table A.13, we list countries that could have the largest positive effect on emerging market venture capital, according to our estimates.

4.3 Falsification tests

There are two remaining potential concerns with the interpretation of our estimates of Equation 2, presented in Tables 3 and 4. First, similarity to China, as we measure it, may be spuriously correlated with similarity to other countries. Second, 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.

We address these concerns with a series of falsification tests. To address the first concern, we successively compute the similarity of each $country * sector$ to its counterpart in *every* other country. We then estimate a series of versions of Equation 2 in which we replace $ChinaSuitability_{cs}$ with the analogous suitability measure for every other country around the world. If our estimates are truly driven by the rise of China and economic similarity to China, we would expect our main coefficient estimate to be in the right tail of the coefficient distribution.

Figure 9a presents the histogram of placebo coefficients in green and our main coefficient estimate from Table 3 with a vertical red line. Reassuringly, the placebo coefficients centered near zero and our main estimate is the largest. These results are consistent with an interpretation of our main results as the sector-specific consequences of the suitability of Chinese businesses.

To address the second concern, we again estimate a series of placebo versions of Equation 2, now randomizing the sectoral component of $ChinaSuitability_{cs}$ within each country. For example, for the Agriculture Tech macro-sector in Pakistan, we assign the China suitability score of one of Pakistan's 15 major sectors at random. We repeat this procedure for all country-sector pairs each time we estimate Equation 2. Figure 9b presents the histogram of these placebo coefficients in green and our main coefficient estimate from Table 3 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.

4.4 Alternative empirical strategy: early unicorns in China

As an alternative empirical strategy to identify the consequences of the rise of Chinese venture activity, we exploit the emergence of successful companies in China early in the sample period as a shifter 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 unicorns fell, and which subsequently attracted follow-on investments, was highly idiosyncratic. Put another way, early success in China is 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.[35] Columns 1 and 2 of Table 5 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. Next, in columns 3 through 6 of Table 5, we repeat the baseline estimates from Tables A.2 and 3, replacing the sector-level China-led indicator with each of the two measures of early Chinese success. The results are strongly positive and significant in all specifications. These estimates are consistent with a causal interpretation of our baseline results.

4.5 The US as a venture capital benchmark

To this point, our analysis has focused on how the rise of China re-shaped global entrepreneurship. We have not directly investigated the role of the US as the original benchmark country. Is it true that, prior to the rise of China, economic similarity to the US was a strong determinant of global venture investment? And did the relative importance of the US decline as China grew?

To investigate these questions, we construct a sector-by-sector measure of similarity to the US ($USSuitability_{cs}$), constructed analogously to the measure of $ChinaSuitability_{cs}$ described in Section 3.3. We then investigate whether this measure predicts global entrepreneurship at the country-by-sector level prior to the rise of China, and whether its predictive power declines over time in the sectors that China came to dominate.

First, we focus on years before 2013 and investigate the relationship at the country-by-sector level between the number of deals and both $USSuitability$ and $ChinaSuitability$. In particular, we estimate:

$$y_{cs} = \phi_1 USSuitability_{cs} + \phi_2 ChinaSuitability_{cs} + \alpha_c + \gamma_s + \epsilon_{cs}, \quad (3)$$

where ϕ_1 captures the effect of US suitability on pre-period deals and ϕ_2 captures the effect

[35] 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 financing of unicorn firms (typically defined as those with a nominal valuation of greater than one billion dollars Davydova et al. (2022)).

of China suitability on pre-period deals. Figure 10a displays the estimate of ϕ_1 and it is positive and significant ($\phi_1 = 1.255$, $p = 0.030$), indicating that economic similarity to the US was a strong predictor of investment prior to 2013. Figure 10b displays the estimate of ϕ_2 and it is small in magnitude, negative in sign, and statistically indistinguishable from zero ($\phi_2 = -0.528$, $p = 0.316$). These estimates suggest that the US, and not China, was a relevant benchmark for VC investment prior to 2013.

Second, we investigate whether the importance of the US as a VC benchmark declined over time in the sectors led by China. In particular, we estimate an augmented version of Equation 2 that also includes a triple interaction between $ChinaLed_s$, $Post_t$, and $USSuitability_{cs}$. A negative coefficient on this triple interaction would indicate that US suitability became a weaker predictor of VC activity after China's rise and in the sectors dominated by China. The coefficient on this triple interaction is displayed in Figure 11, both for the un-weighted (11a) and weighted (11b) specifications. In both cases, it is negative and statistically significant ($p = 0.020, p = 0.010$). The absolute value of the coefficient is about a third the size of the effect of China suitability in Table 3.

Thus, consistent with qualitative accounts, during the early part of the sample period economic similarity to the US was a strong predictor of venture activity. As China rose as a source of start up business models, the importance of the US as a benchmark country declined substantially. This was particularly in the sectors led by China.

5 Mechanisms

5.1 Mirroring Chinese business models

The findings from the previous section documented that emerging market entrepreneurship grew disproportionately in sectors led by China. This pattern is driven by country-sector pairs where social and economic indicators suggest that Chinese technology would be most "suitable." Our hypothesis is that part of this pattern is driven by entrepreneurs in suitable country-sector pairs not just emulating the industries of ventures in China, but also adapting businesses that were successful in China.

Methods In order to capture direct emulation of Chinese companies, we use Natural Language Processing (NLP) tools to measure similarity in business description across all company pairs within each sector. 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.[36] Using this method, we 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.[37] 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.[38]

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.

Results Table 6 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 magnitude is even larger when focusing on the right tail of the company similarity distribution (column 2). Thus, not only did suitable

[36] 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.

[37] Byju's business description is "Developer of an online learning platform intended to deliver engaging and accessible education. The company's platform makes use of original content, watch-and-learn videos, animations, and interactive simulations that make learning contextual, visual, and practical, enabling students to receive a personalized educational experience." Yuanfudao's business description: "Developer of an online educational platform designed to provide online tutoring services for Chinese students. The company's one-stop online tutoring platform provides elementary school, junior high school, and high school students with various lessons that cover all subjects, enabling students to know their learning weaknesses and conduct targeted learning by leveraging big data analysis."

[38] Yundee's business description is "Provider of an Augmentative and Alternative Communication (AAC) application intended to help children with autism that have difficulty with speech. The company's Augmentative and Alternative Communication (AAC) application can also be used as a tool parents and teachers use to teach children communication and cognitive skills, it is an open source application allowing it to be adapted to different languages in order to reach even more families around the world, enabling Autistic children better communicate their wants and needs in school and at home."

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. 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, and these effects remain driven by country-sector pairs where Chinese businesses have the highest predicted suitability.

5.2 Who receives investment and who are the investors?

We next investigate which firms and types of investors drive the main result.

First, 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 there is a greater willingness to fund startups in China-led sectors, having witnessed the success of similar companies in China. Alternatively, the funding may be concentrated in later-stage companies, perhaps as more sophisticated or globally connected firms "pile in" to finance these firms.

Table 7 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 "suitable" emerging markets. The growth of initial funding opportunities seems to be an important mechanism driving the baseline result.

Next, we investigate which types of investors drive the main results. The nature of who provides the funding is a critical question and again, there are several possible answers. One possibility is that investment in China-led sectors is driven by Chinese investment firms themselves, who may try to replicate their domestic successes by investing in similar sectors or companies abroad. For instance, among the investors in Indian education companies were Tencent's corporate venture fund and Hong Kong-based SAIF Partners. Such a result might have substantial implications for the governance and flow of profits from these firms. Alternatively, these firms could be primarily attracting funds from local groups or from third countries, who deduce that these business models will be good fits and re-direct their own portfolios accordingly.

Table 8 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. Beyond re-shuffling the types of companies being started, these estimates indicate that the growth of Chinese venture capital promoted local investment in emerging markets.

5.3 Is it the politics, stupid?

Our results suggest that Chinese entrepreneurs focus on developing technology and business models that would work well in China and that, as a result, may also have broader applications in emerging markets. However, the fact that this “appropriate enrepreneurship” mechanism underlies our baseline results should not be taken for granted. In particular, politics also may 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).

First, it is possible 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. It may be that China’s political allies are more likely to emulate Chinese models of entrepreneurship. Second, the direction of entrepreneurship in China has been driven in part by top-down initiatives that target key strategic sectors. It is possible that these political initiatives are, in part, responsible for the development 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;[39] and *(ii)* the similarity of political regime types 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.[40]

We also compiled lists of strategic technologies from two of the high-profile technological blueprints laid out by the Chinese government: *(i)* "Made in China 2025" (published in 2015), a national strategic plan and industrial policy as part of China’s Thirteenth and Fourteenth Five-Year Plans; and *(ii)* "China’s Stranglehold Technologies" (published in 2018), a list of China’s most vulnerable technology choke points where China is critically dependent upon US, Japanese, and European suppliers and for which producing Chinese substitutes is explicitly called for by China’s Ministry of Science and Technology. We then hand-linked each of the technologies on these lists to one or more of the sectors in our baseline analysis.

[39]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. Using these tools, we assess both domestic institutions and international interactions to understand countries’ political alignment both cross-sectionally and over time.

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

To understand whether politics shapes our baseline results, we estimate versions of Equation 2, restricting the sample to countries that are either China's friends or enemies, and restricting the sectors to strategic and non-strategic technologies.

Table 9 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. Thus, while China's allies seem to be slightly more likely to follow Chinese entrepreneurship when it is locally suitable, there are also large effects of Chinese entrepreneurship models on non-allies.

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 connectedness to China could be an independent mechanism leading to the diffusion of Chinese entrepreneurship. We estimate a version of Equation 2 in which we also include $ChinaLed_s * Post_t$ interacted with both UN voting distance from China and Polity score distance to China. The estimates are reported in Table 10. We estimate a negative coefficient on both terms, 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 the coefficient estimate on the suitability interaction, indicating that the diffusion of "appropriate entrepreneruship" operates independently from political ties.

6 Broader impacts

In this section, we investigate the broader economic impacts of the rise of Chinese VC on emerging market entrepreneurship. On the one hand, by choosing a more appropriate set of entrepreneurial models, new ventures in emerging markets may be able to become more innovative, generate more jobs, 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 Outcomes of firms that received venture funding

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), suggesting that nothing relevant was learned from the rise of China? Or are they driven by businesses that end up being successful? To investigate this question, we use data from PitchBook 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 11 presents 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 1, 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. This result suggests that the findings are not driven by unsuccessful companies. In column 2, 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 3, 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. That said, the story of many of these companies remains to be written. Many of the consequences of the rise of emerging market venture capital will be determined in the years to come.

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 next investigate whether our findings are accompanied by repeat entrepreneurship and investment. We then investigate whether these serial entrepreneurs and investors were indeed 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.

More concretely, we estimate versions of the following augmented version of our baseline specification:

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

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.[41] 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 they fall into, and separately estimate the effect on serial entrepreneurs whose second companies fall into sector grouping X, where

$$X \in \{\text{All China-Led, Some Not China Led, All Not China Led}\}^{42}$$

Table 12 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. Even more importantly, 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 with at least one company falling into a sector that is not led by China, and the coefficient estimate is positive and significant. Finally, in column 4, the outcome variable is the number of entrepreneurs with *all* of their companies falling into sectors that are not led by China. The coefficient is again positive and significant. We observe a similar pattern in columns 5-8, where the outcome variable is an indicator for the presence of any serial entrepreneur in the relevant category.

These findings suggest that while serial entrepreneurs are most likely to emerge from China-led sectors, they end up exploring sectors that are less likely to have a Chinese benchmark or clear 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.

Next, we repeat this analysis focusing on serial *investors*.[43] Appendix Table A.14 follows the same structure as Table 12, except all outcomes focus on serial investors instead

[41] 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.

[42] 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.

[43] Some investors will by definition be serial investors: e.g., a fund that exclusively focuses on Indian fintech firms. But many funds have the ability to "skip around" between sectors and countries.

of serial entrepreneurs. These findings are less clear: the coefficient estimates are positive in all specifications, however the estimates are less precise. Nevertheless, when we focus on serial investors in sectors that are not China led (columns 4 and 8), we estimate positive and significant effects. These findings indicate that investors who first gained experience in China-led sectors may also extend their investments in subsequent years to local businesses in other sectors.

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).

We next investigate whether the rise of China led to the growth of geographic hubs of VC investment 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-led sectors.

In particular, 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 the city i and year t.[44] 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.

The results are presented in Table 13. In Panel A, all outcomes are normalized counts (as in our baseline analysis); in Panel B they are inverse hyperbolic sine transformed; and in Panel C they are logged. In all cases, the story is similar.

[44]We geo-locate the headquarters of all VC-backed companies in the PitchBook database using SimpleMaps data as main data source and supplement with Opendatasoft data. 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 database's 1:10 million data, which includes 7,342 cities and towns across the world. The selection of cities, according to Natural Earth, not only focuses on the absolute population of the city but also on the regional significance (for example, all country capitals and most regional capitals are always included) to ensure the sample is representative. 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.

We first restrict attention to cities in emerging economies. In column 1, the outcome variable is the number of companies founded. 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.

We find positive effects on *both* companies that are in China-led sectors and companies that are not. While intuitively the effect size is larger for companies in China-led sectors, it is positive and statistically distinguishable from zero for companies outside China-led sectors, indicating that there may have been positive local spillovers from entrepreneurship that directly followed Chinese business models. These findings dovetail with the results from the previous section, which documented the rise of serial entrepreneurs who branched out from the sectors in which their first companies were founded.

In column 4, we use the full sample of countries and investigate whether, as in the country-by-sector-level analysis, the positive effect of the rise of China on local entrepreneurship is larger in developing compared to developed countries. We include an interaction between $ShareChinaLed_i * Post_t$ and the emerging market indicator. We 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 of this rise in VC activity on patenting, one proxy for overall innovative activity, by looking at the number of patents whose assignee organizations are located in the city. 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.

Figure 12 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.

Taken together, these estimates suggest that the rise of Chinese entrepreneurship had impacts beyond the companies that it directly inspired. In cities that were initially best positioned to follow China, there was substantial business formation in sectors that were *not* dominated by China, as well as an increase in overall patenting activity.

7 Conclusion

The paper investigates the implications of the rise of the Chinese venture capital industry — an unprecedented case in the developing world — on entrepreneurship in emerging economies. Using a variety of empirical approaches, we find consistent evidence that the creation of an alternative model of entrepreneurship (relative to that in the US) facilitated the funding of more numerous and more appropriate entrepreneurial firms in the developing world.

These findings raise a variety of questions for future research. The first is to better understand the welfare implications of such a shift. Offering alternative models of entrepreneurship that are more appropriate to developing country needs may be unquestionably beneficial. However, the entrepreneurial success of Chinese business models may also lead to relatively 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 (see Senor and Singer, 2009). Understanding the consequences of Chinese entrepreneurial success and its diffusion for "soft power" is an important question, if a difficult one to satisfactorily address.

Second, our study ends in 2020, which may have marked the end of the golden era of venture investments 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. Among the key steps have been the discouragement of investments and public offerings in sectors such as social media and education technology, accompanied by the dramatic influx of government funds into local venture groups. As a result, many venture firms have swung to "politically correct" investing (in the words of Neil Shen, the managing partner of HongShan, formerly Sequoia China), with an emphasis on technologies directly aligned with government objectives.[45] As the results in Section 5.3 suggest, this shift may make China far less relevant as a role model for aspiring entrepreneurs in other countries. Investigating the global consequences of this recent turn in Chinese venture capital strikes us as an important area for future work.

[45] 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`.

Finally, our study is a first step towards systematically evaluating the benefits and drawbacks of a US-led system of innovation and entrepreneurship, especially from the perspective of developing countries. It suggests there may be some value in modifying the existing system so that it at once maintains the benefits of economies of scale and (reasonably) well-aligned incentives between entrepreneurs, investors, and the ultimate asset owners, while also funding appropriate businesses for all parts of the world. How entrepreneurship can help realize the human and social capital in emerging economies is a trillion dollar question, with much of the humanity's growth potential depending on the answer.

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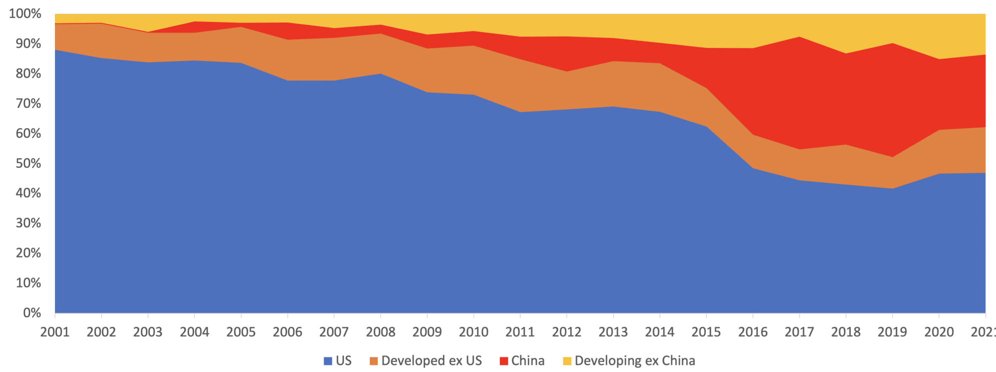
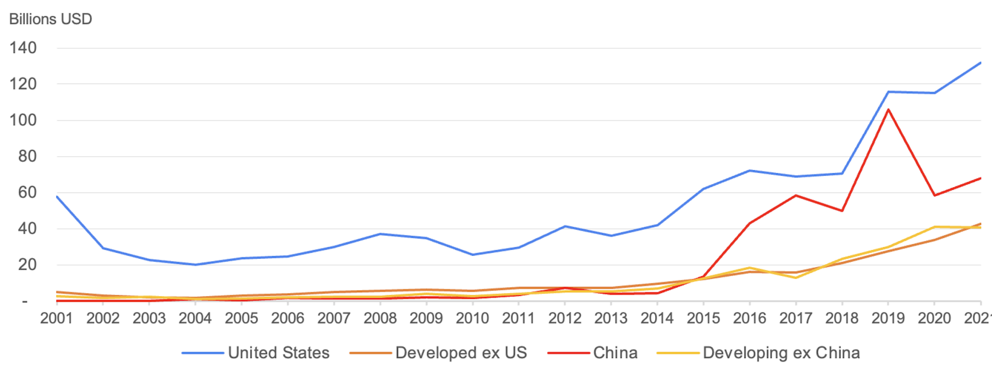
Figures

Figure 1: Venture Investment Overview

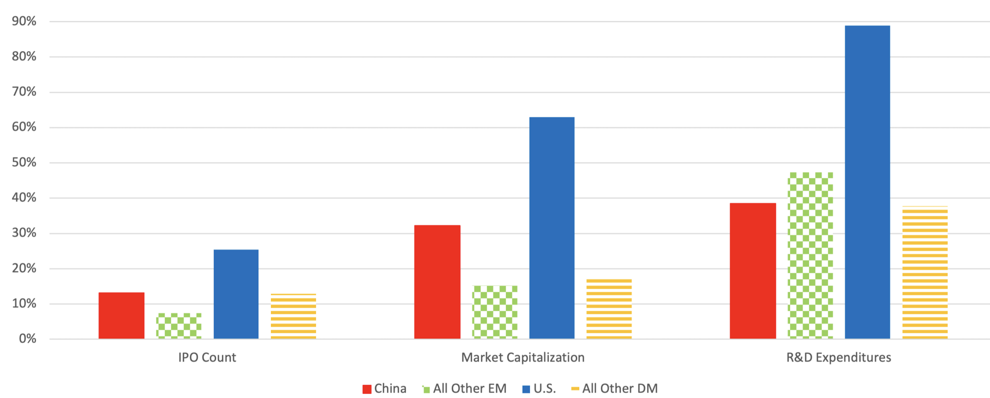
(a) Share of Global VC Investment



(b) Value of Global Investment

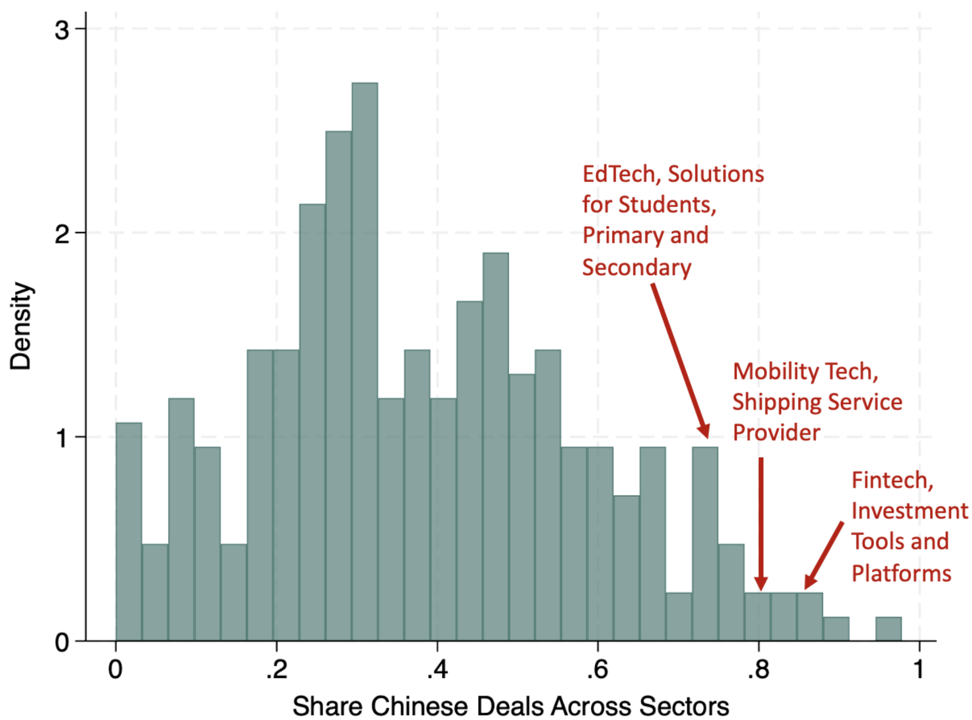


(c) VC-Backed Firms as a Share of Young Public Firms



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.

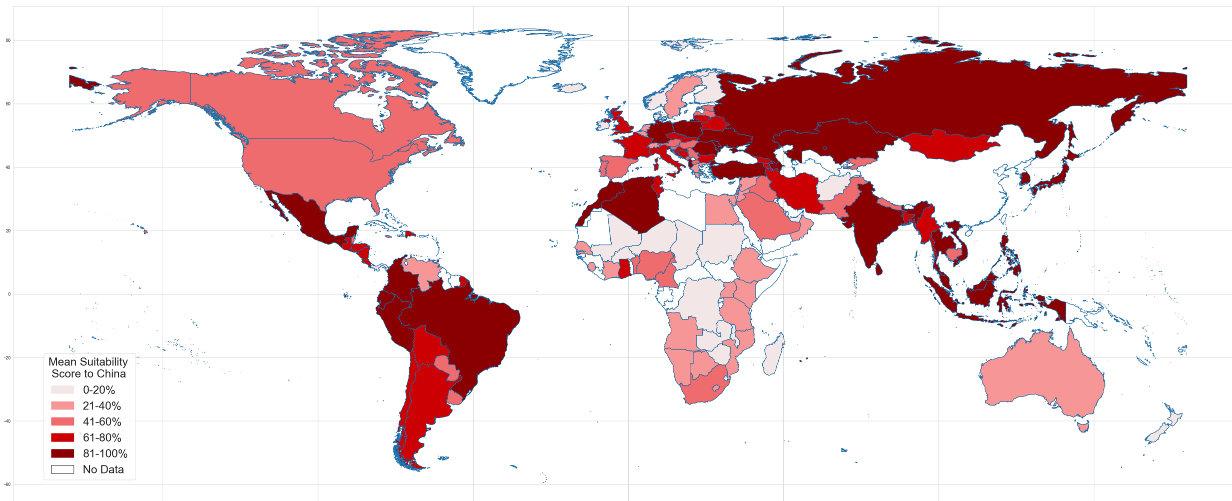
Figure 2: China's Share of Venture Deals Across Sectors



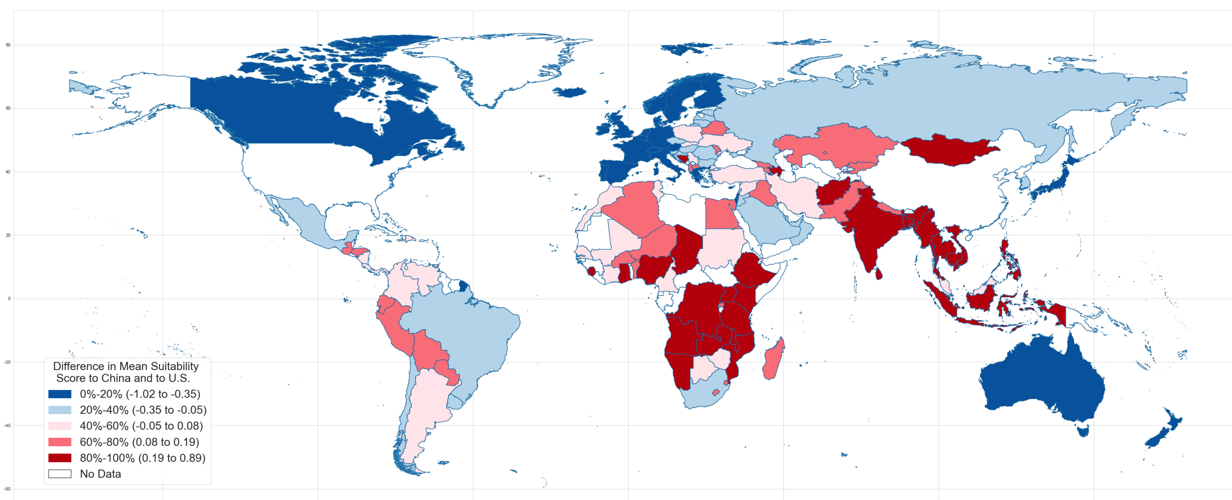
Notes: This figure plots a histogram of the ratio of the number of venture deals for Chinese companies to the total number of venture deals for Chinese and US companies in each sector from 2015 to 2019. Values for three example sectors are marked in red.

Figure 3: Country-Level Variation in Business Suitability

(a) Average China Suitability



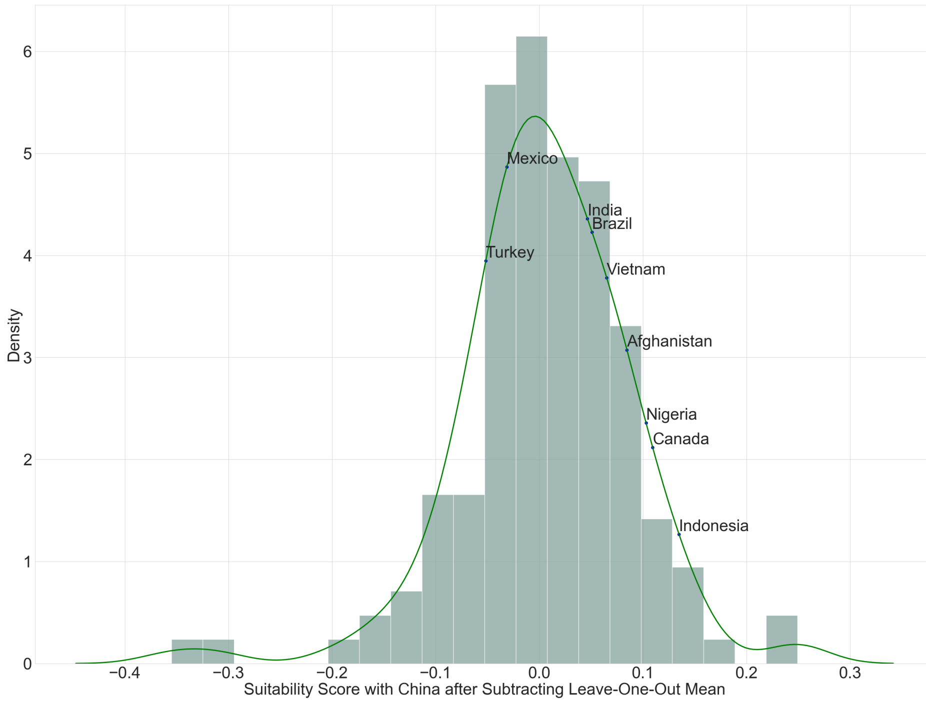
(b) Difference Between Average China Suitability and Average US Suitability



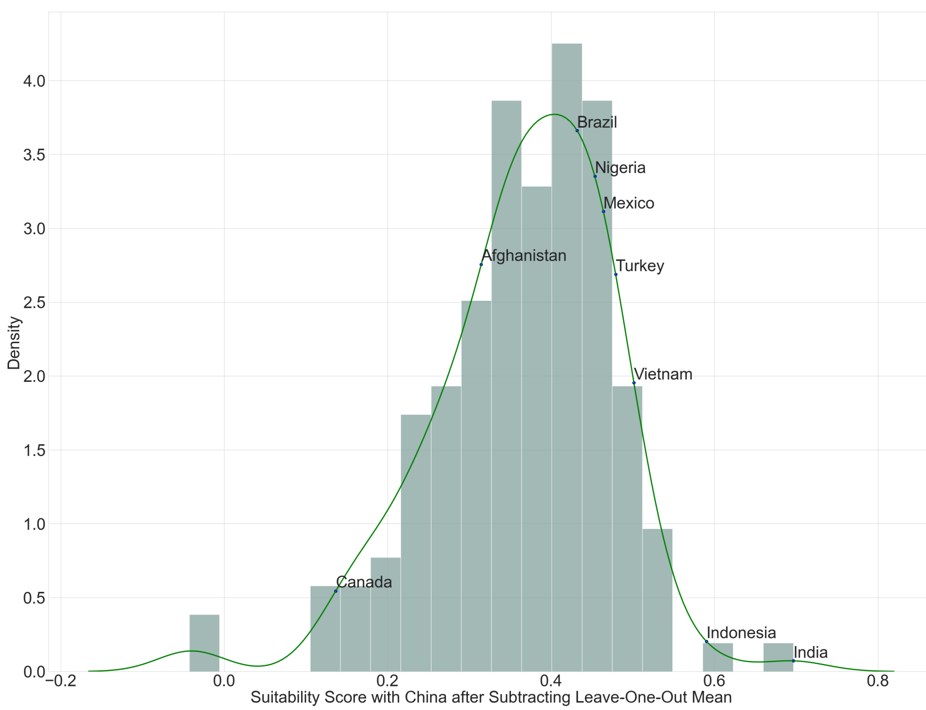
Notes: Figure 3a displays a world map in which each country is color-coded based on its average China suitability, where the average is taken across all fifteen macro-sectors weighted by their share of global pre-period investment. Darker-colored countries are in higher quintiles of the China-suitability 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: Within-Country, Sector-Level Variation in Business Suitability

(a) AgTech



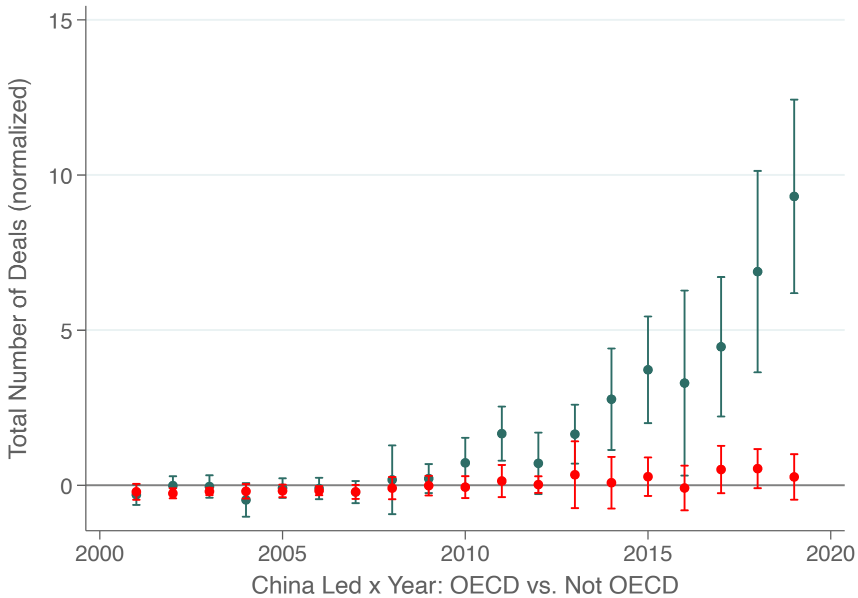
(b) FinTech



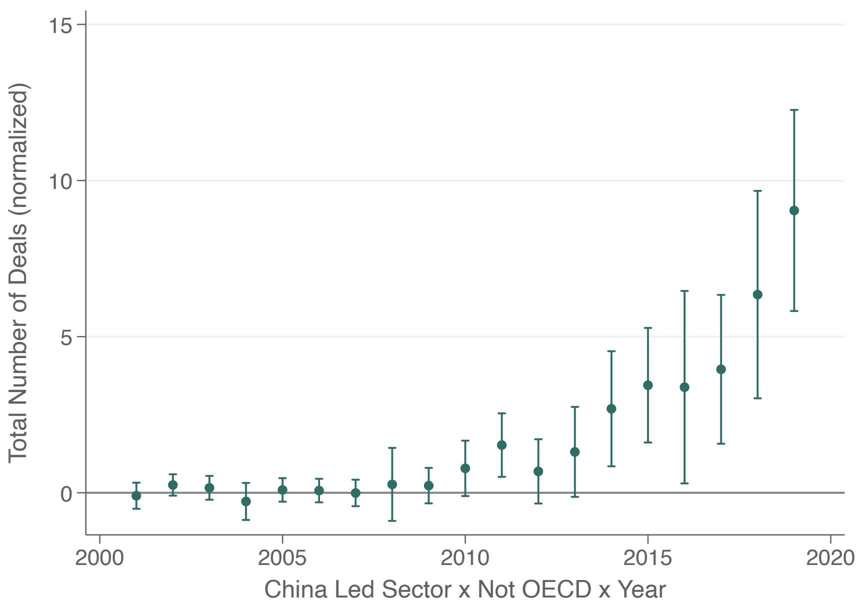
Notes: Figure 4a displays histogram of each all countries' China-suitability in the AgTech macro-sector, after subtracting average China suitability across all other macro-sectors. Figure 4b displays the same for FinTech.

Figure 5: Dynamic Effects: EM Investments Follow China

(a) Double-Difference Estimates



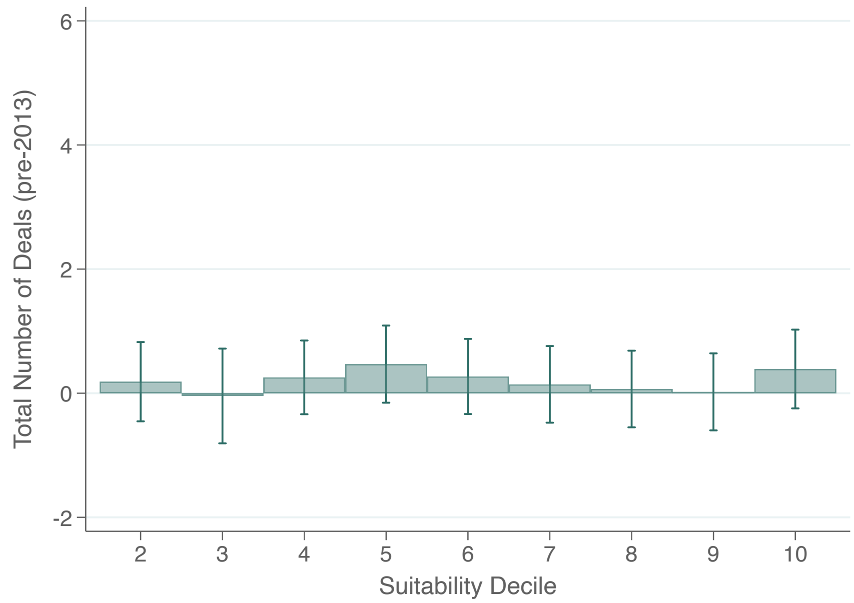
(b) Triple-Difference Estimates



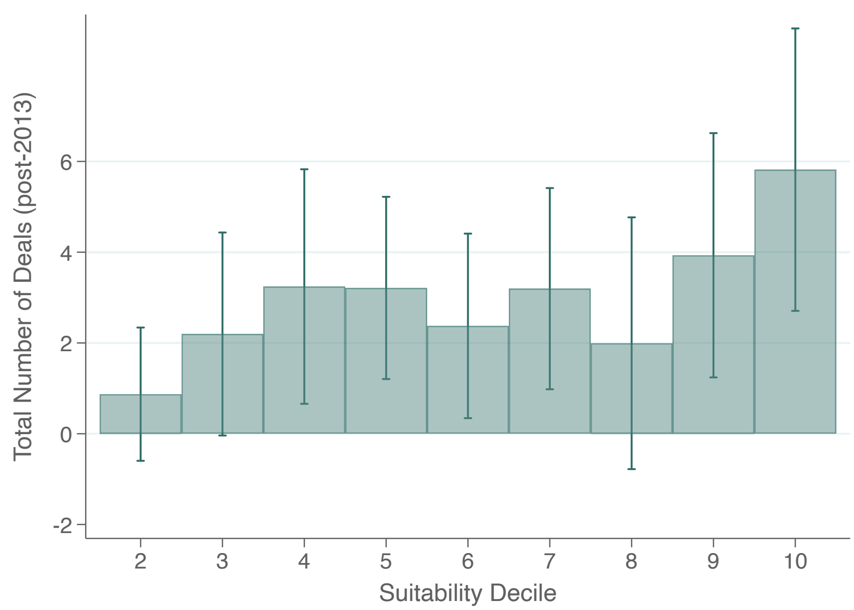
Notes: Figure 5a shows estimates of year indicators interacted with $ChinaLed_s$, separately for countries in the OECD by 1980 (red) and countries outside the OECD in 1980 (green). Figure 5b displays triple-difference estimates of year indicators interacted with $ChinaLed_s * EM_c$. The year 2000 is the excluded category in both figures. Standard errors are clustered by country and 90% confidence intervals are reported.

Figure 6: Suitability Effects by Decile: Pre vs. Post Peirod

(a) Pre-period (before 2013)

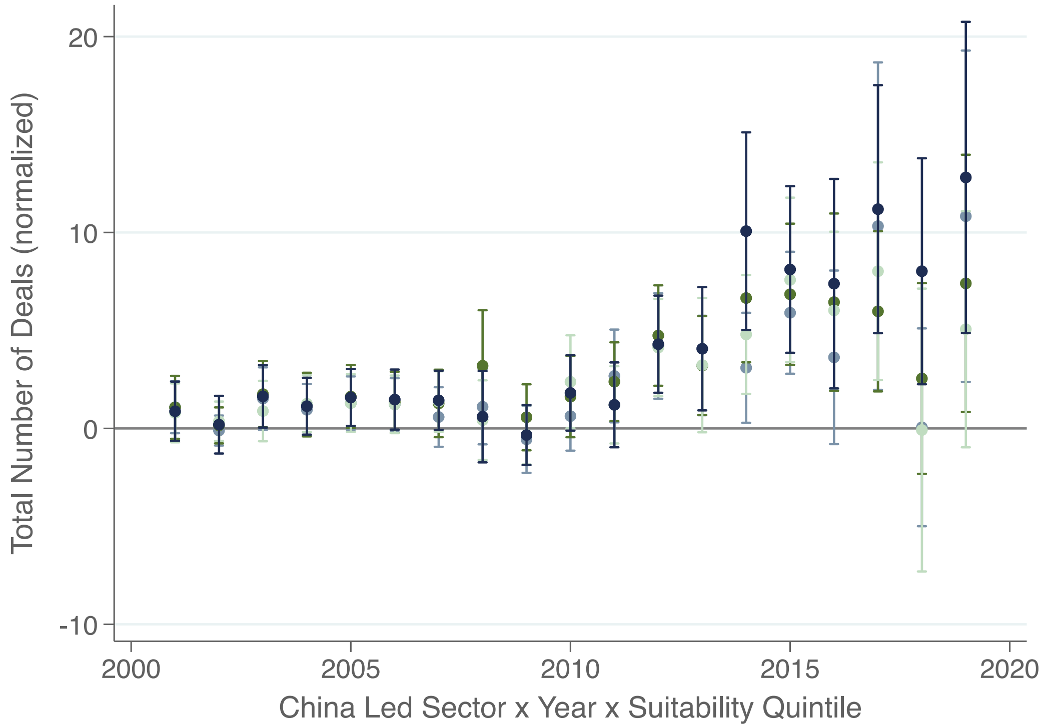


(b) Post-period (after 2013)



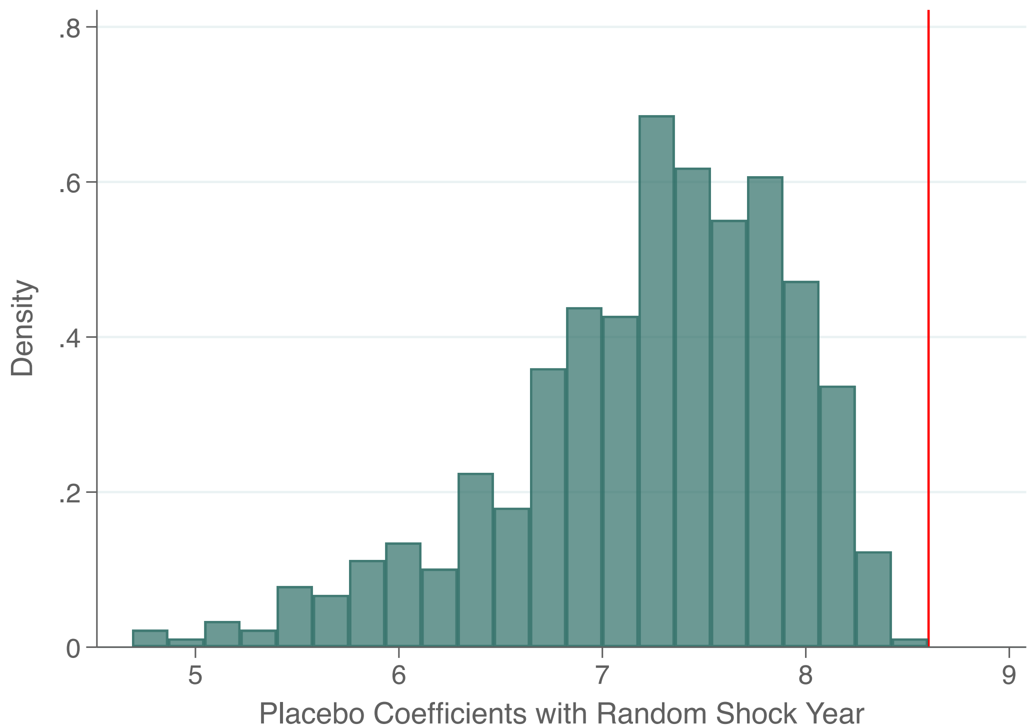
Notes: Figure 6a shows estimates of suitability decile indicators interacted with $ChinaLed_s$, and the outcome variable is total (normalized) deals in the country-sector during the pre-period. Figure 6b shows estimates of suitability decile indicators interacted with $ChinaLed_s$, and the outcome variable 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: 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.

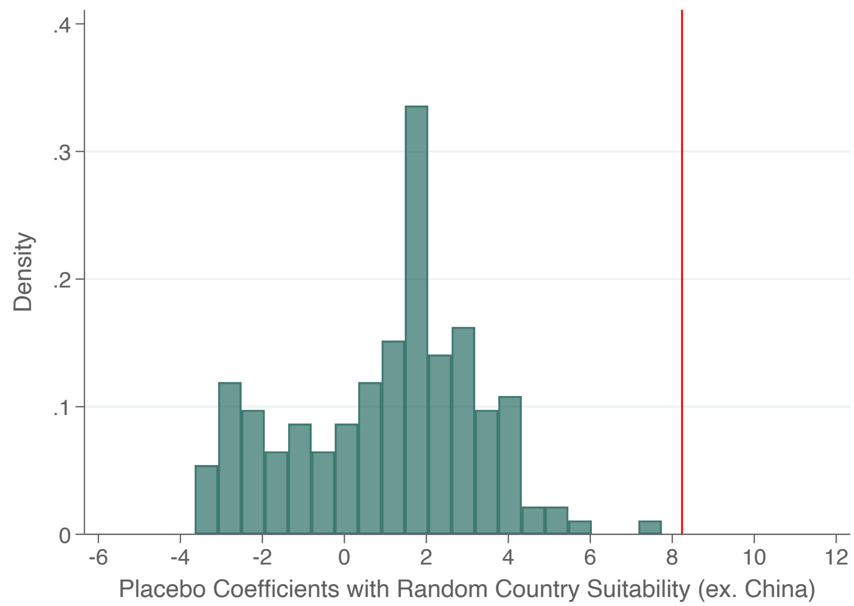
Figure 8: Suitability and Venture Activity: Sector-Specific Timing



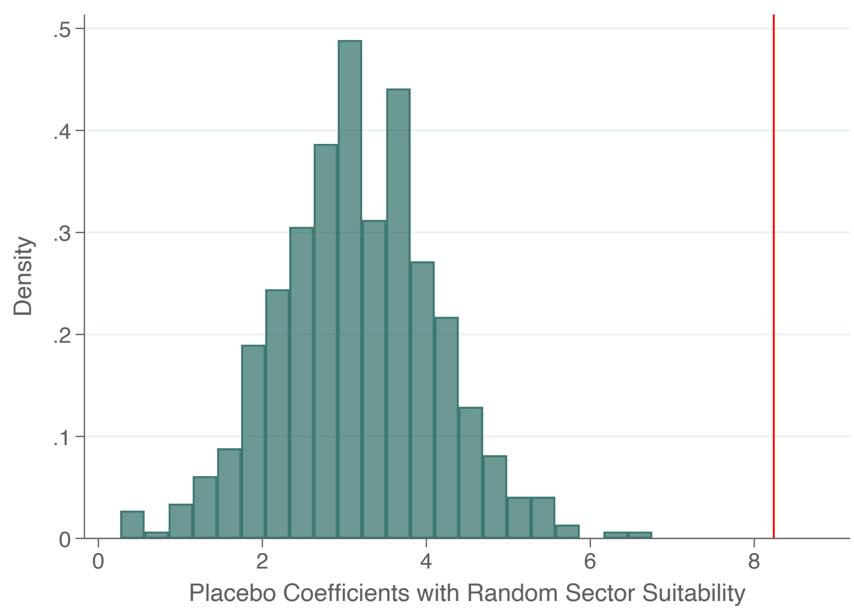
Notes: The red vertical line displays our main estimate of β from Equation 2 in which $Post_t$ is replaced with a sector-specific post period indicator. The histogram displays coefficient estimates from 500 regressions in which the surge year was chosen randomly for each China-led sector (but the number of sectors assigned to each year was held constant).

Figure 9: Falsification Tests

(a) Random Country Placebo



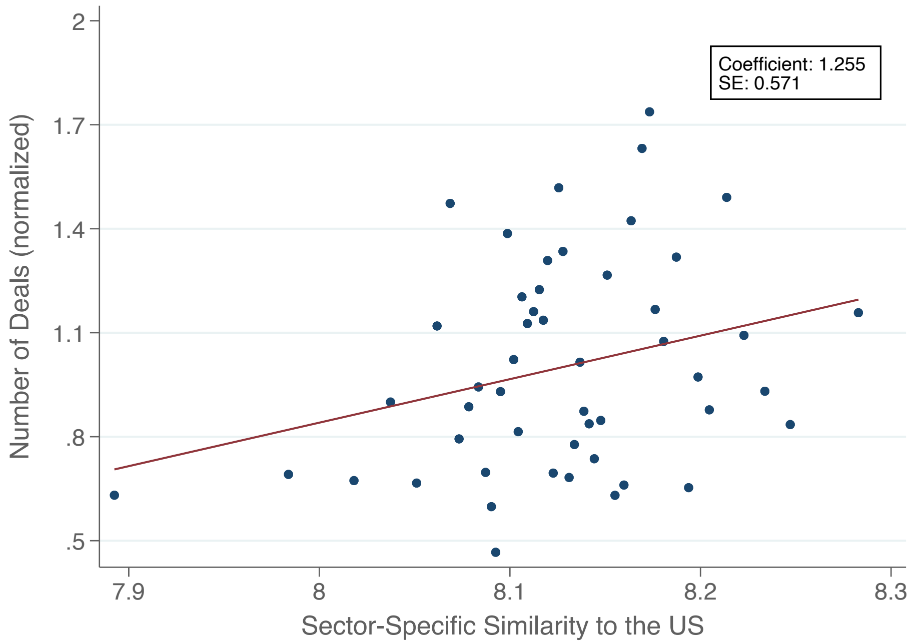
(b) Random Sector Placebo



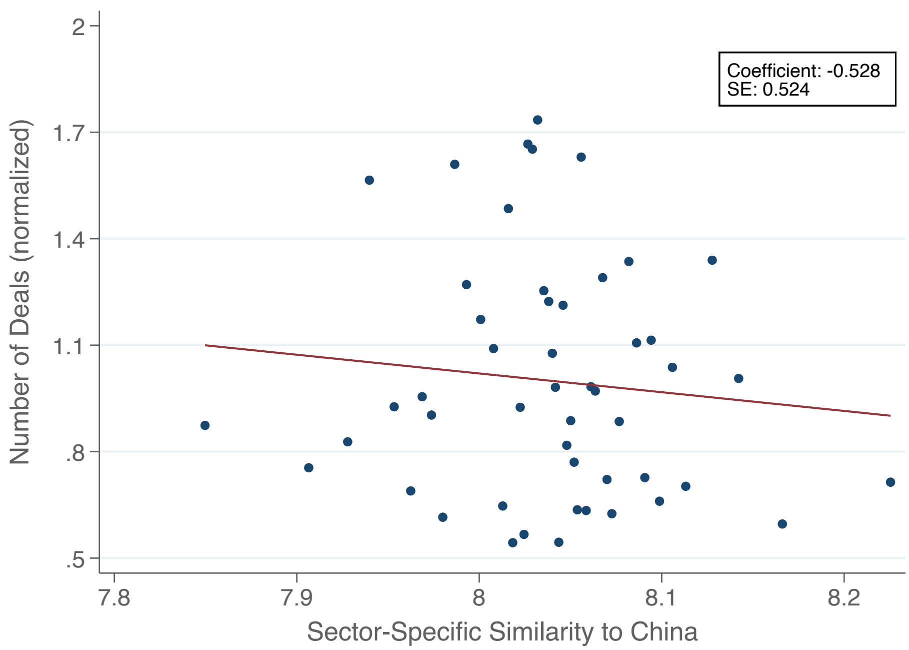
Notes: Figure 9a reports a histogram of coefficient estimates from a series of estimates of Equation 2, in which $ChinaSuitability_{cs}$ is replaced with an analogous suitability measure for each other country. Our main estimate of β from Equation 2 is displayed with a red vertical line. Figure 9b reports 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. Again, our main estimate of β from Equation 2 is displayed with a red vertical line.

Figure 10: US vs. China Suitability Before China's Rise

(a) US Suitability and Pre-2013 Deals



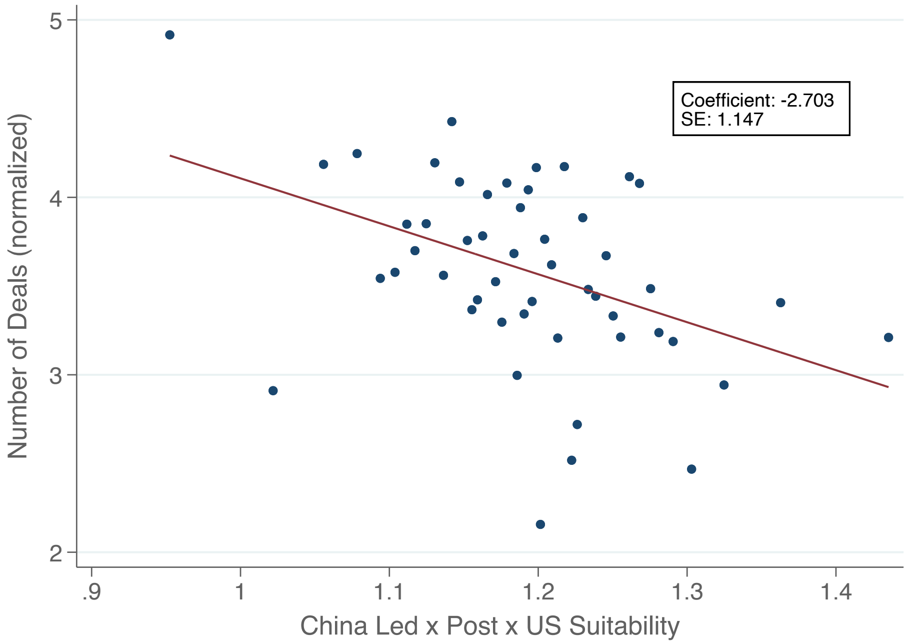
(b) China Suitability and Pre-2013 Deals



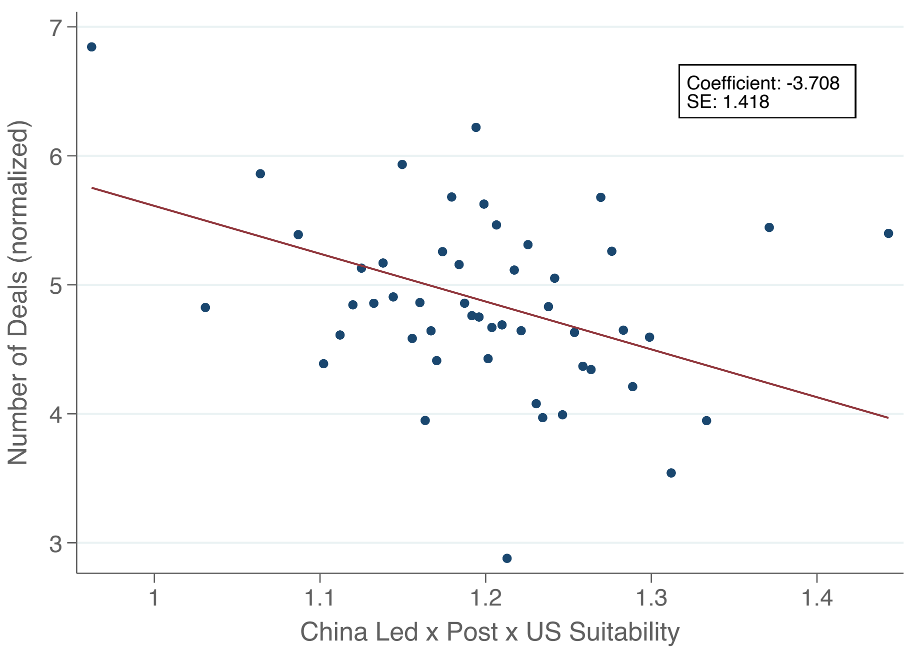
Notes: Figure 10a shows the relationship between pre-2013 deals and $USSuitability_{cs}$ while Figure 10b shows the relationship between pre-2013 deals and $ChinaSuitability_{cs}$. The outcome variable is the number of deals, summed from 2000-2012 and normalized relative to the country mean, as described in the main text.

Figure 11: US Suitability After China's Rise

(a) Unweighted



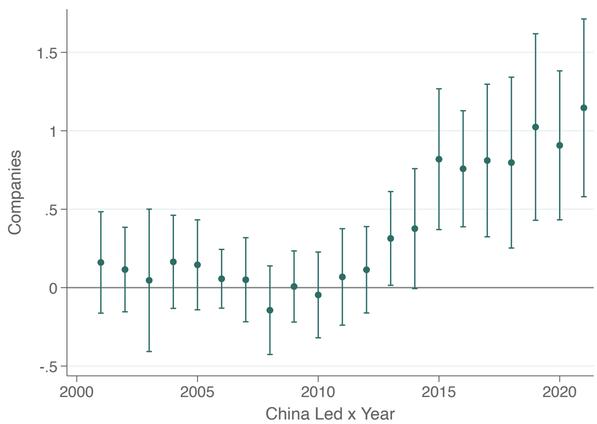
(b) Deal Count Weighted



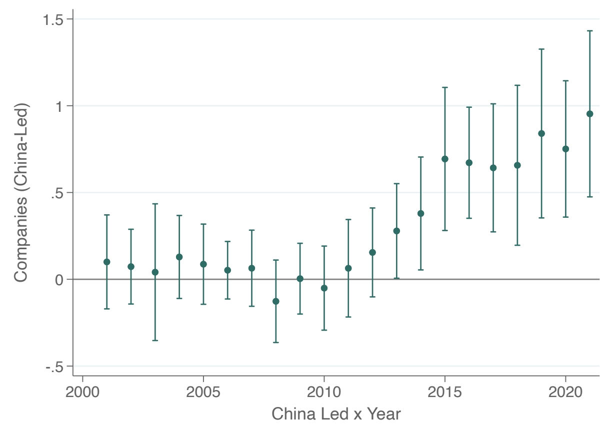
Notes: Both figures display partial correlation plots of the relationship between normalized deal count and the triple interaction between $ChinaLed_s$, $Post_t$, and $USSuitability_{cs}$. All specifications also include the full set of two-way fixed effects, as well as the baseline independent variable of interest (the triple interaction between $ChinaLed_s$, $Post_t$, and $USSuitability_{cs}$). Standard errors are clustered by country.

Figure 12: China's Rise and City-Level Entrepreneurship: Dynamics

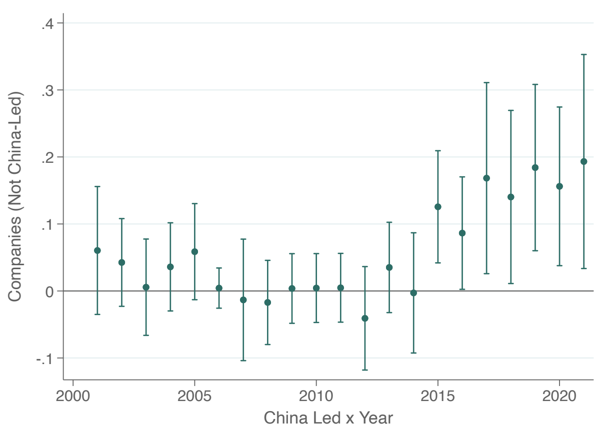
(a) Companies (All)



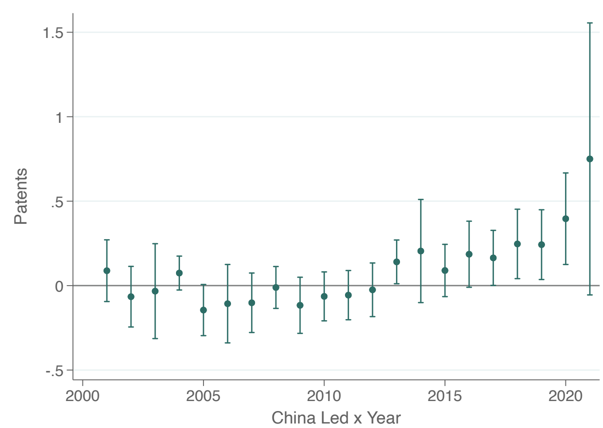
(b) Companies (China-led Sectors)



(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.

Tables

Table 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 2: Summary Statistics

Panel A: VC Deals					
	Total	China	United States	Other EM	Other Non-EM
Number of VC deals	179,899	30,788	82,109	18,945	48,057
Number of companies with VC deals	94,169	16,266	36,943	12,336	28,624
Mean size of VC deals (US$ millions)	13.55	28.73	13.86	13.20	6.89
Mean number of VC deals per company	1.91	1.89	2.22	1.54	1.68
Share of companies with > 1 deal	44.12%	49.19%	51.86%	30.38%	37.17%

Panel B1: Sectors				
	Mean	Median	SD	Count
Number of companies per sector	1021.14	415.50	1942.41	266
Number of predicted sectors per company	3.08	3.00	1.64	88267
Number of sectors conditional on >1 sector	3.51	3.00	1.47	72943

Panel B2: Sectors, Divided by China and U.S. Led		
	China-led Sectors	US-led Sectors
Total number of companies	136,908	134,715
Total number of companies (other EM)	19,715	15,110
Total number of companies (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 United States. The time-span for all panels is from 2000 to 2019. Panel A reports summary statistics on venture capital (VC) deals extracted from PitchBook. All deal size information is nominal U.S. dollars. Panel B1 reports summary statistics on sectors. Panel B2 reports summary statistics on China-led sectors and U.S.-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 U.S. companies for 2015-2019 is above the median among all sectors. Similarly, U.S.-led sectors are sectors that are below the median of the aforementioned ratio.

Table 3: Suitability of Chinese Technology Increases Entrepreneurship

	Dependent Variable: Number of Deals (Normalized)			
	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Bottom Quartile Suitability	Top Three Quartiles Suitability
China-Led Sector × Post × China Suitability	8.238***	7.827**		
	(2.902)	(3.023)		
China-Led Sector × Post × EM			0.149	4.976***
			(1.697)	(0.961)
Sector × Country Fixed Effects	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes
Sector × Year × EM Fixed Effects	No	Yes	No	No
Number of Obs	552300	552300	124440	475200
Mean of Dep. Var	3.588	3.588	3.033	3.726
SD of Dep. Var	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 4: 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	8.238***	10.477***	0.102**	0.179**	0.225*
	(2.902)	(3.729)	(0.044)	(0.081)	(0.116)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	11.050***	14.495***	0.131***	0.262***	0.434***
	(3.324)	(4.522)	(0.031)	(0.079)	(0.145)
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	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 U.S. 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 5: Alternative Empirical Strategy: 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 6: 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 Fixed Effects	Yes	Yes
Country × Year Fixed Effects	Yes	Yes
Sector × Year Fixed Effects	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 7: New versus Existing Companies

	Outcome is the (normalized) number of	
	(1) First deals for a company	(2) Follow-on deals
China-Led Sector × Post × China Suitability	5.295***	2.943**
	(2.006)	(1.201)
Sector × Country Fixed Effects	Yes	Yes
Country × Year Fixed Effects	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes
Number of Obs	552300	552300
Mean of Dep. Var	2.772	0.816
SD of Dep. Var	39.463	17.930

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 8: Source of Investors

	(Normalized) Number of Deals from		
	(1) Investors from US	(2) Investors from China	(3) Investors from Own Country
China-Led Sector × Post × China Suitability	1.087	0.880	4.455***
	(1.295)	(0.565)	(1.604)
Sector × Country Fixed Effects	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes
Number of Obs	552300	552300	552300
Mean of Dep. Var	0.803	0.079	1.716
SD of Dep. Var	19.497	4.150	26.571

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 9: The Effect of Political Alignment

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

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 10: Results after Controlling for Political Alignment

	Dependent Variable: Number of Deals (Normalized)			
	(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 11: Effects by Company Outcome

	Outcome is (normalized) number of deals for companies that end up		
	(1) Failure	(2) Acquired/ IPO	(3) Neither (yet)
China-Led Sector × Post × China Suitability	0.525	1.204**	6.510***
	(0.791)	(0.557)	(2.241)
Sector × Country Fixed Effects	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes
Number of Obs	552300	552300	552300
Mean of Dep. Var	0.507	0.496	2.584
SD of Dep. Var	16.311	13.803	38.142

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 12: 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 × China Suitability	0.019**	0.005	0.014**	0.006*	0.012***	0.005*	0.009**	0.005*
	(0.008)	(0.003)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Sector × 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. Founders are coded as "only in CL sectors" if their second companies only fall within the China-led sectors (as defined in our main analysis), as "any non-CL sectors" if their second companies fall outside the China-led sectors, and as "only non-CL sectors" if their second companies fall entirely outside the China-led sectors. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 13: China's Rise and City-Level Entrepreneurship

	All Companies	Companies in China-Led Sectors	Companies in 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 of 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 of 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 of 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 of 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 of 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 of 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 2001 to 2021, we use a tabulation of our own PitchBook data.

Since PitchBook did not begin data collection until 2007, years before 2001 seem to have severe "backfill bias." For data from 1969 to 2000 (used only in Table 1 and Figure A.2), we tabulate data from the Refinitiv (also known as 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 mid-2022 data PitchBook 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]

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:

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

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

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

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 latest release of the Maddison Project Database, which provides information on comparative economic growth and income levels over the very long run. The project is aimed at standardizing and updating the academic work in the field of historical national accounting in the tradition of the syntheses of long-term economic growth produced by Angus Maddison in the 1990s and early 2000. The 2020 version of this database covers 169 countries. The table presents Purchasing Power Parity-adjusted GDP per capita in 2011 US dollars.

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

Appendix 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.

[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).

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).

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.7 and Appendix Table A.8, we show the baseline results are robust to the two broader indicator assignment strategies.

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

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

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

Since this "taking the mean" measure to tackle missing values will inevitably reduce cross-country variation when missing values are prevalent, we apply thresholds to drop certain countries and indicators with poor data availability. Specifically, in our baseline analysis in the paper, for the set of indicators that are assigned to at least one macro-sector, we first drop countries that have at least 25% of the indicators missing. This procedure mainly rules out overseas territories, small island countries, and other countries that have low data availability. Then, we remove indicators that are missing in at least 20% of the remaining countries. As a result, there are 74, 105, and 827 indicators being used in the final 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.9, A.10, A.11, and A.12, 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, 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 3613. The percentage increase induced by China's effect is 3613/(9130-3613) = 65%. 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%.

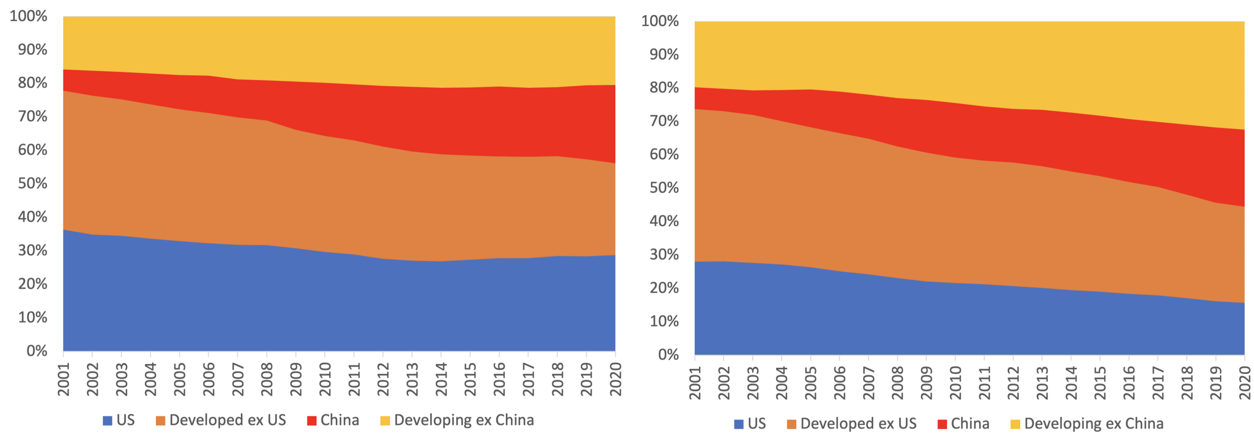
Second, we simulate the hypothetical case of another country X's rise in place of China to evaluate the relative importance of China's rise. We show two versions of the calculation: (i) with a fixed number of country-led sectors and (ii) with a GDP-adjusted number of country-led sectors, where we scale 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 relative suitability similarity for other countries with respect to the hypothetical country X. We assume the same coefficients we obtained from China's specification and predict in this hypothetical country X's case what the number of deals will be, taking the mean of the results from the 500 sets of simulated sectors. 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, determine 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 25% 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 8%, followed by Germany and India. In Appendix Table A.13, we list countries with the highest percentage increase in this simulation exercise.

Appendix E Additional Figures and Tables

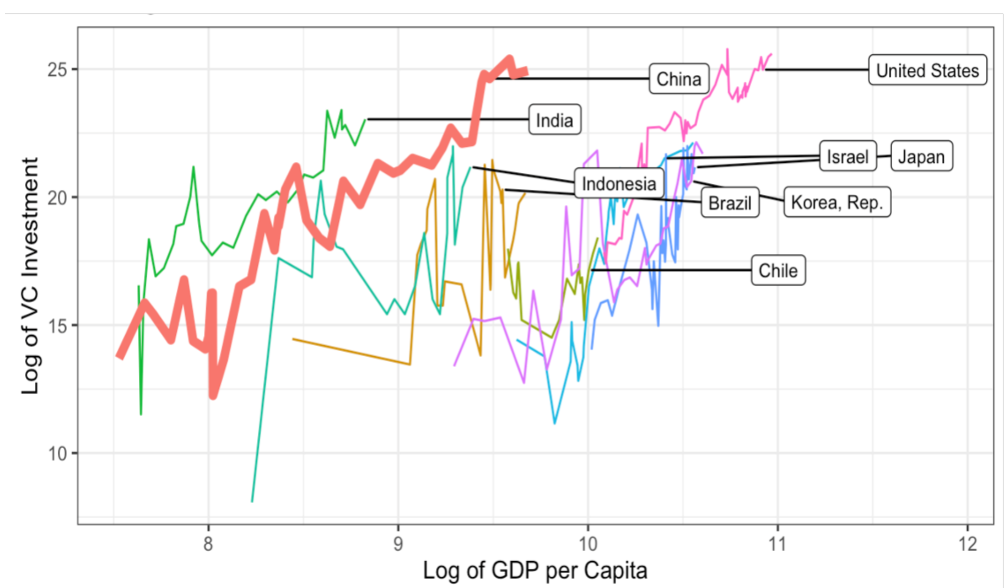
Figure A.1: Global Innovation Overview

(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.

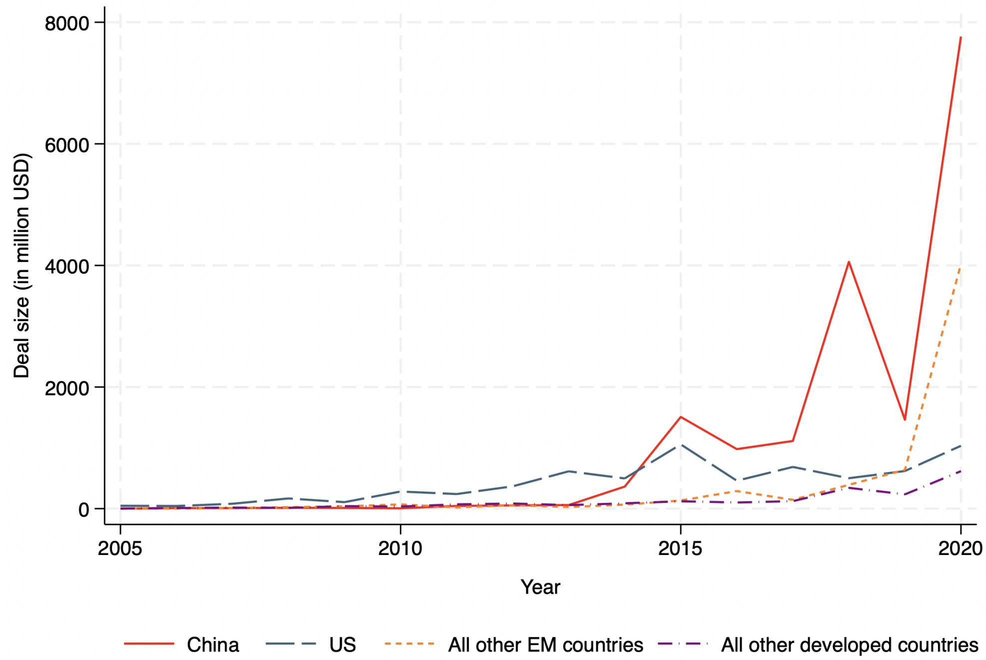
Figure A.2: Venture Investment and GDP Per Capita



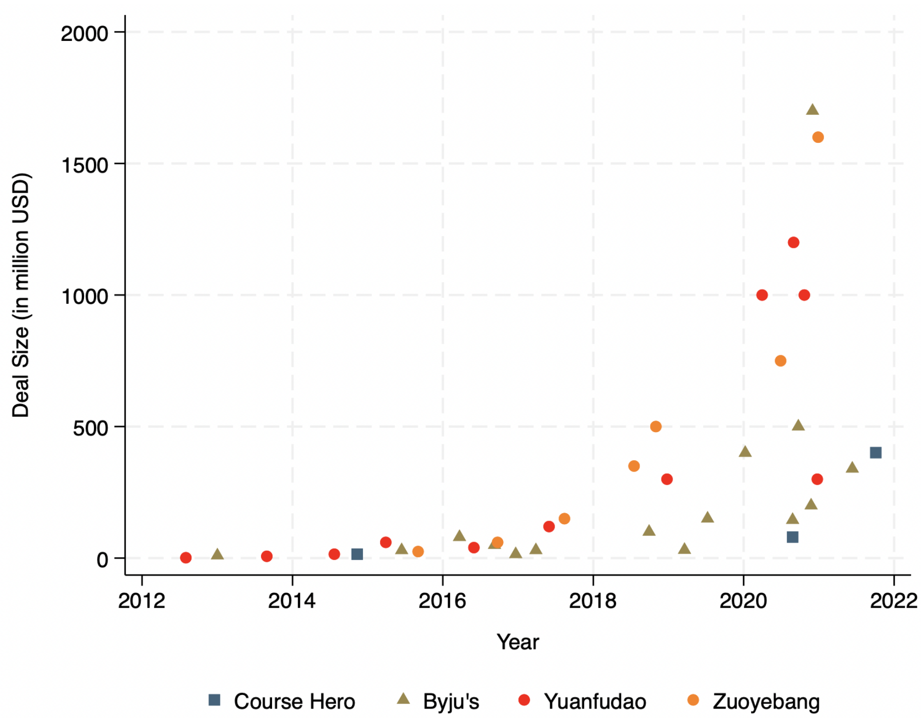
Notes: This figure shows countries' growth in terms of GDP per capita and their venture investment over as long a time period as the data permit. The data sources for this figure are discussed in Appendix A.

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

(a) Cumulative Annual Transaction Volume

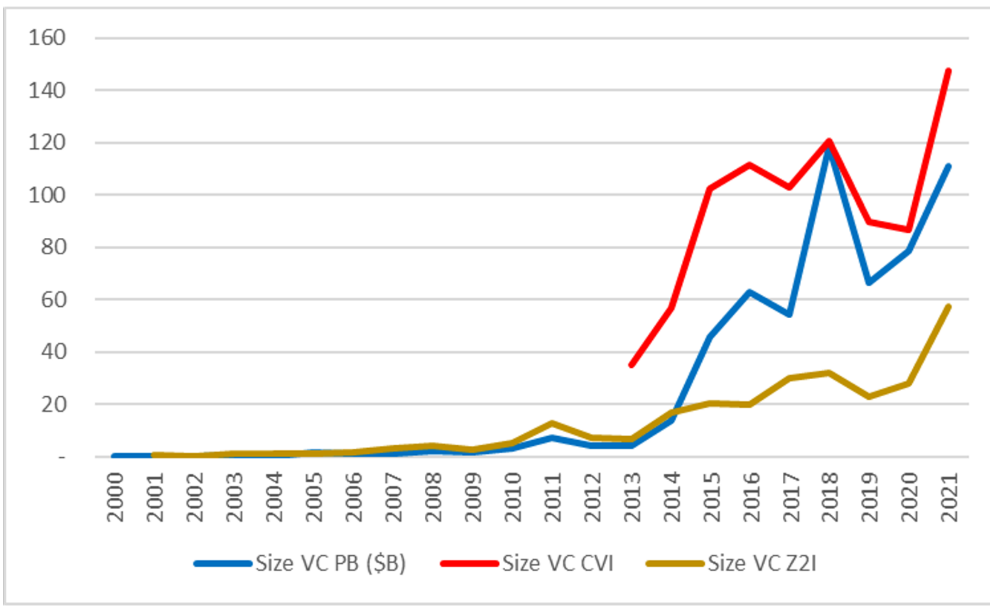


(b) Scatter Plot of Deal Size and Deal Date



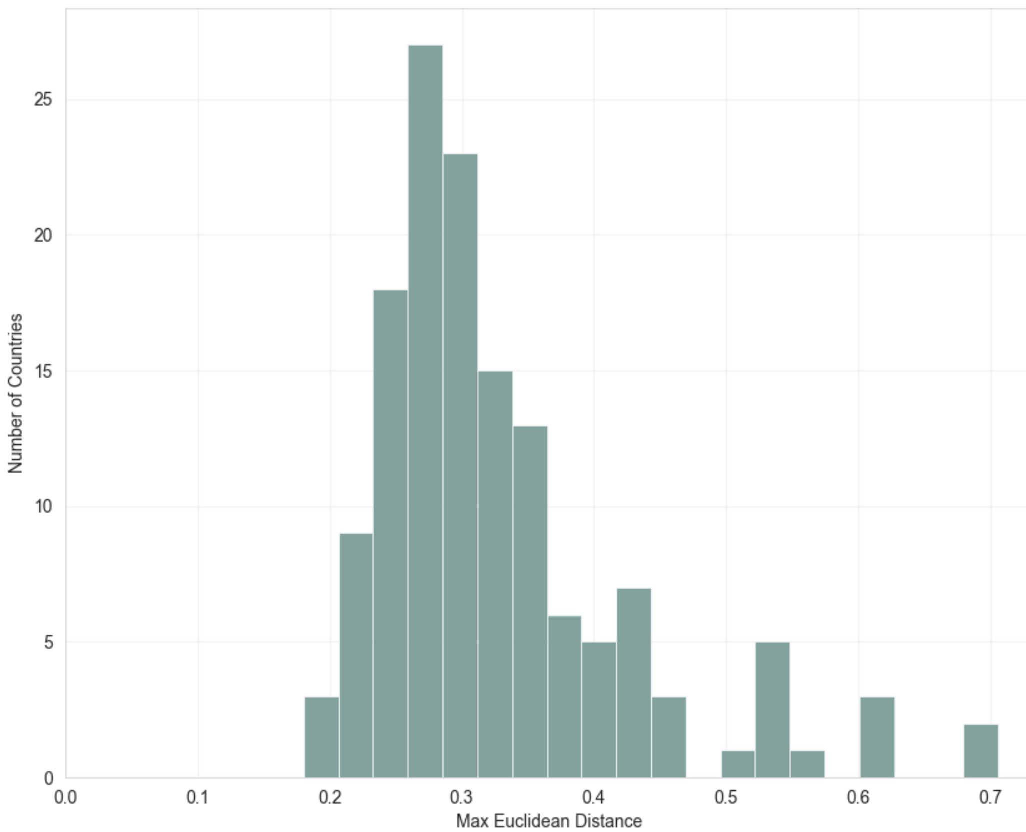
Notes: Figure A.3a displays the cumulative annual transaction volume for China, US, all other emerging countries, and all other developed countries for the sector "Education Technology for Primary and Secondary Students." Figure A.3b shows all funding deals for four major companies in the sector, where 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



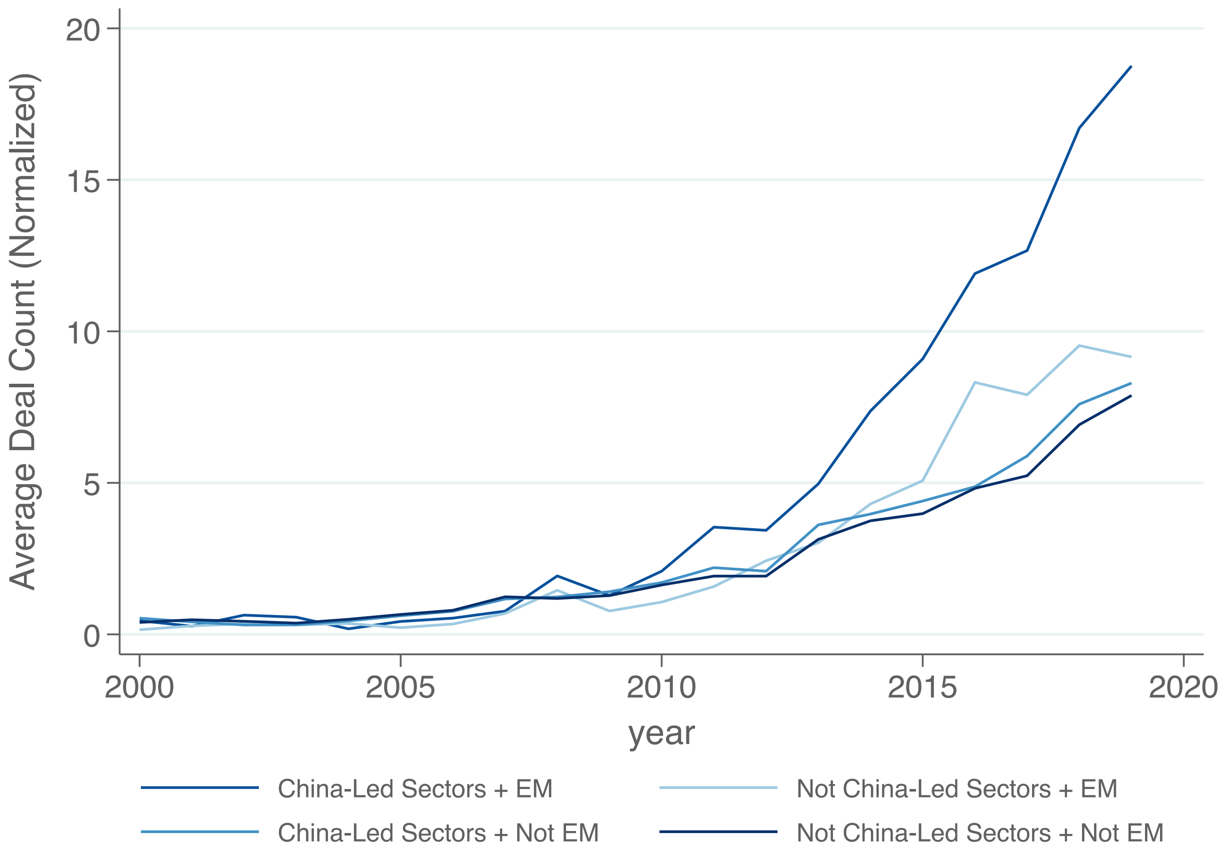
Notes: This figure shows VC transactions in China for three sources: PitchBook, Zero2IPO, and China Venture Institute. Further discussion of the data validation process is in Appendix B.

Figure A.5: Maximum Suitability Score Distance between Sectors within Countries



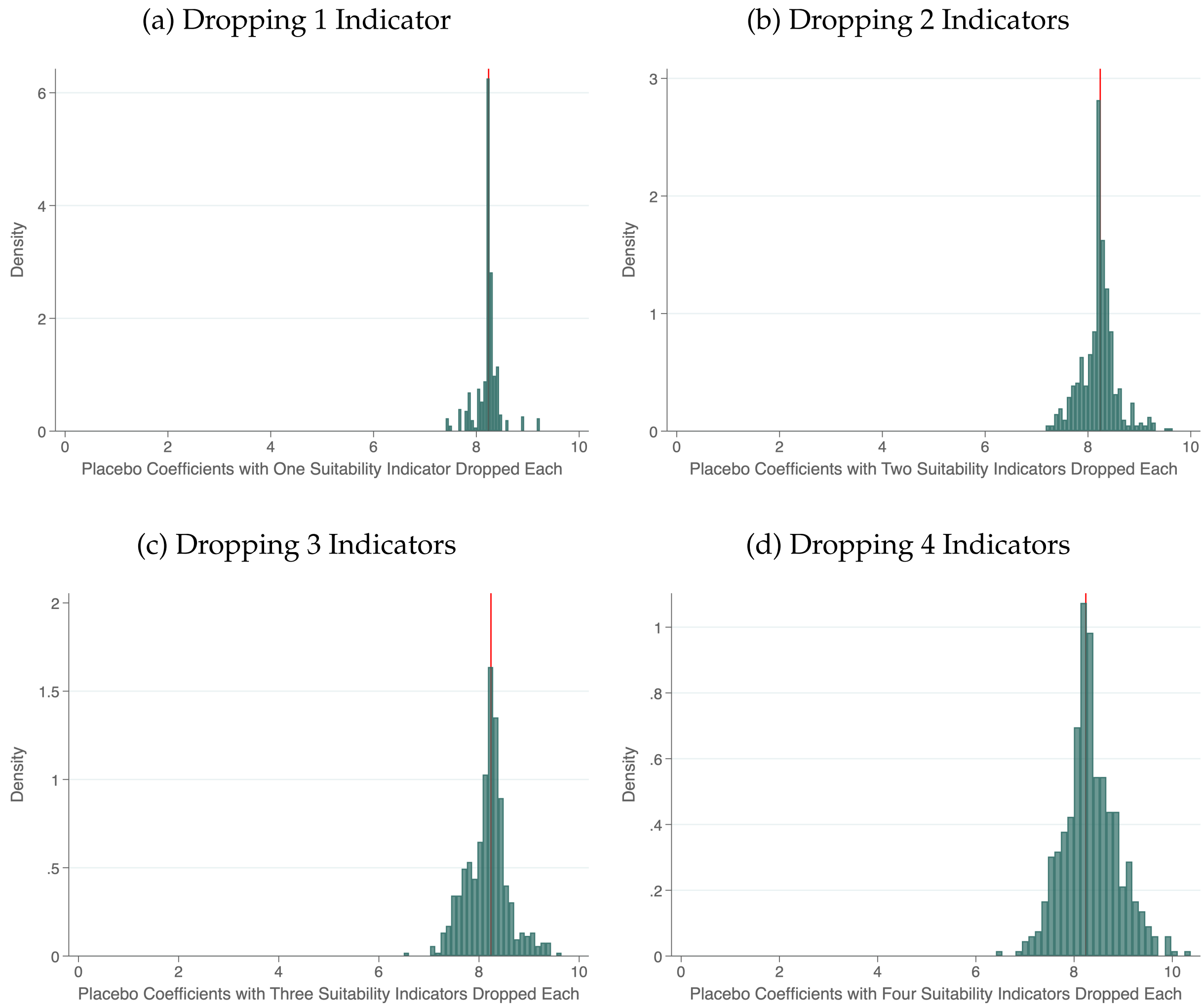
Notes: This figure displays a histogram of the maximum distance between the China-suitability measure of two macro-sectors for all countries.

Figure A.6: Raw Trends in Venture Investment



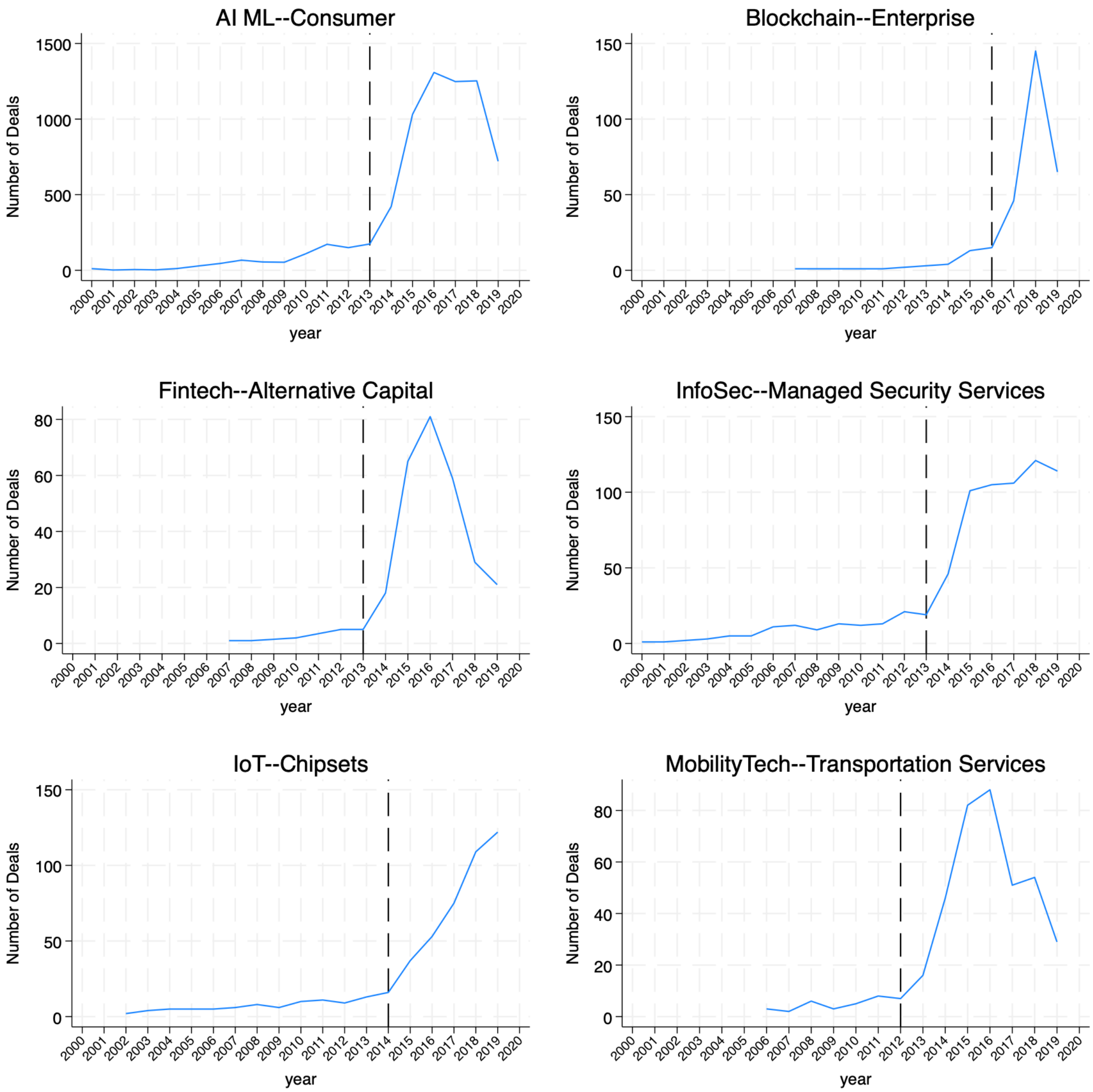
Notes: This figure shows the trend of normalized deals for global markets. The number of deals is normalized by the average amount of deals in the pre-period. Trends are reported separately for China-led and non-China-led sectors, and for deals in emerging and developed markets.

Figure A.7: Robustness to Excluding Indicators from Suitability Measure



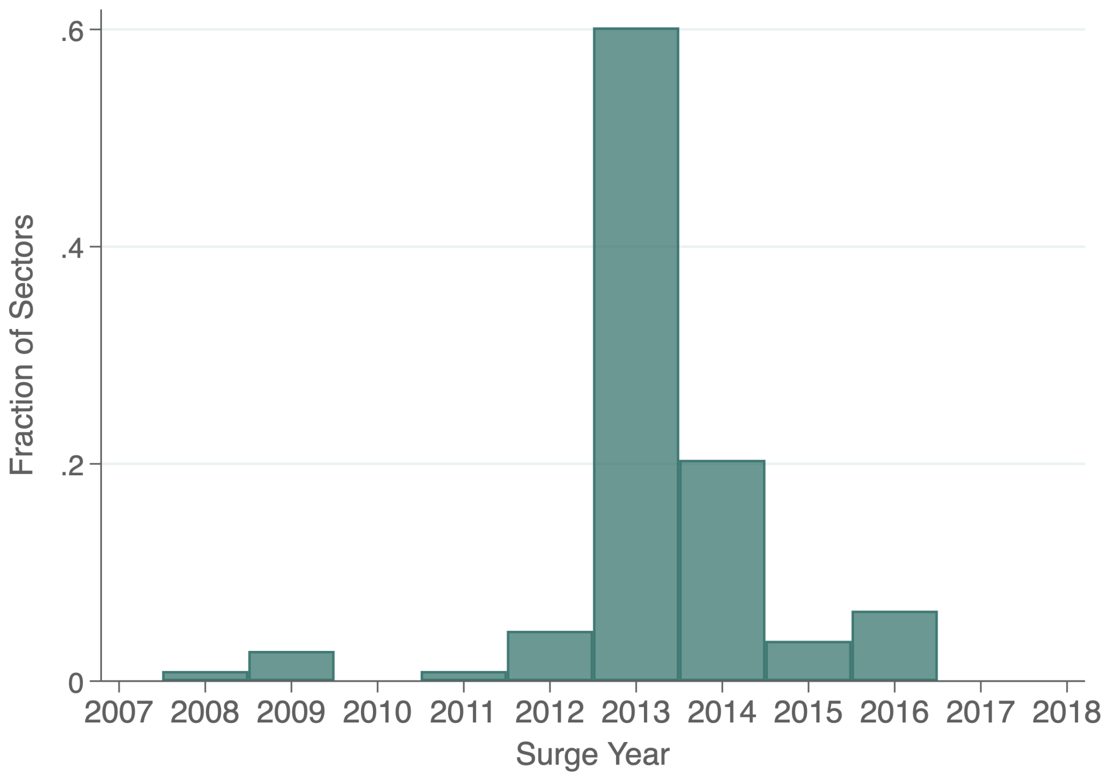
Notes: This figure reports histograms of coefficient estimates from a series of estimates of Equation 2, in which $ChinaSuitability_{cs}$ is replaced with an alternate suitability measure where one, two, three, or four of the indicators used in the suitability calculation are dropped, repeated with 500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

Figure A.8: Examples of Sector-Level Surge Years



Notes: This figure shows 6 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) 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.9: 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."

Table A.1: Example Indicators for Macro-Sectors

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

Notes: This table presents examples of indicators assigned to five macro-sectors. The macro-sector name is listed at the top of each column.

Table A.2: Rise of China Increases Emerging Market Entrepreneurship

	Dependent Variable: Number of Deals (Normalized)				
	(1)	(2)	(3)	(4)	(5)
	Full Sample	Full Sample	Full Sample	EM Only	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.3: Suitability and Entrepreneurship: Robustness for 2000-2021 Sample

	Deal Count			Deal Size	
	(1)	(2)	(3)	(4)	(5)
	Baseline	Weighted	asinh	asinh	log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	9.277**	11.640**	0.109**	0.199**	0.245**
	(3.713)	(4.683)	(0.048)	(0.096)	(0.116)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	12.326***	16.424***	0.144***	0.315***	0.506***
	(3.968)	(5.463)	(0.032)	(0.086)	(0.133)
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	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 U.S. 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.4: Suitability and Entrepreneurship: Robustness for *Relative to the World* Measure

	Deal Count			Deal Size	
	(1)	(2)	(3)	(4)	(5)
	Baseline	Weighted	asinh	asinh	log(per deal)
China-Led Sector × Post × China Suitability	8.606***	11.338***	0.083**	0.133**	0.101
	(2.578)	(3.504)	(0.037)	(0.062)	(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
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 companies in the rest of the world 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 companies in the rest of the world. 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.5: 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	3.278	3.866	0.133**	0.134	0.075
	(4.245)	(4.711)	(0.055)	(0.110)	(0.202)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	2.892*	3.311*	0.181***	0.169*	0.000
	(1.744)	(1.906)	(0.043)	(0.088)	(0.225)
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	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 U.S. 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. 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.6: 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	8.603**	10.105**	0.097**	0.147*	0.064
	(3.383)	(4.167)	(0.042)	(0.080)	(0.114)
Panel B: Strict China-led measure					
China-Led Sector × Sector-Specific Post × China Suitability	11.511***	14.148***	0.119***	0.221***	0.289**
	(3.674)	(4.807)	(0.032)	(0.081)	(0.143)
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	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.7: 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	8.034***	10.471***	0.080**	0.135*	0.173*
	(2.809)	(3.621)	(0.037)	(0.073)	(0.100)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	10.970***	14.822***	0.119***	0.231***	0.403***
	(3.277)	(4.465)	(0.029)	(0.075)	(0.118)
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	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.8: 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	10.902**	14.656**	0.151***	0.303**	0.495**
	(4.911)	(6.229)	(0.053)	(0.122)	(0.244)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	16.087**	22.571***	0.140***	0.339**	0.991***
	(6.132)	(8.335)	(0.050)	(0.129)	(0.357)
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	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.9: Suitability and Entrepreneurship: Robustness to Dropping Countries with Above 20% Missing

	Deal Count			Deal Size	
	(1)	(2)	(3)	(4)	(5)
	Baseline	Weighted	asinh	asinh	log(per deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × China Suitability	8.936***	11.309***	0.122***	0.210**	0.194
	(3.165)	(4.054)	(0.044)	(0.081)	(0.131)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	12.110***	15.736***	0.143***	0.280***	0.390**
	(3.677)	(4.957)	(0.030)	(0.078)	(0.159)
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	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.10: Suitability and Entrepreneurship: Robustness to Dropping Countries with Above 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	8.118***	10.316***	0.102**	0.179**	0.222*
	(2.883)	(3.705)	(0.044)	(0.081)	(0.114)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	10.925***	14.302***	0.131***	0.261***	0.428***
	(3.295)	(4.487)	(0.031)	(0.079)	(0.144)
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	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.11: Suitability and Entrepreneurship: Robustness to Dropping Indicators with Above 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 $\times$ Post $\times$ China Suitability	8.352***	10.628***	0.103**	0.178**	0.225**
	(2.903)	(3.722)	(0.043)	(0.080)	(0.108)
Panel B: Strict China-led measure					
China-Led Sector (Strict) $\times$ Post $\times$ China Suitability	11.051***	14.536***	0.130***	0.255***	0.433***
	(3.294)	(4.481)	(0.031)	(0.078)	(0.132)
Sector $\times$ Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector $\times$ 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.12: Suitability and Entrepreneurship: Robustness to Dropping Indicators with Above 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	7.669**	9.592**	0.107**	0.182**	0.219*
	(3.045)	(3.913)	(0.043)	(0.079)	(0.128)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × China Suitability	10.871***	14.070***	0.138***	0.268***	0.445***
	(3.548)	(4.776)	(0.030)	(0.078)	(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
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.13: 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.14: Serial Investors

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

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 their companies only fall within the China-led sectors (as defined in our main analysis), as "any non-CL sectors" if at least one of their companies falls outside the China-led sectors, and as "only non-CL sectors" if all of their companies fall outside the China-led sectors. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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