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

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September 15, 2023

Abstract

Global high-potential entrepreneurship investment has traditionally been dominated by rich countries, especially the U.S., until the rise of China as the first developing country to become a venture capital powerhouse. We explore the international ramifications of China's rise for emerging economies' entrepreneurship 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 led by China. This effect was driven by country-sector pairs most economically similar to China. Second, 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. Third, this growth in investment had positive cross-sector and geographic spillovers. Taken together, our findings suggest that developing countries benefited from the rise of China, which led to the development of business models more suited to their local context. A system where only rich countries lead in entrepreneurship could limit the appropriateness of capital allocation and entrepreneurial activity in developing countries.

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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 inappropriate 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 investments 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 U.S. 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 U.S. represented the location of 88% of global venture dollars invested, and other developed countries the majority of the remainder (7%).[3] By 2019, China accounted for over 38% of global venture activities. Thus, this episode presents a singular opportunity to understand the global ramifications of a developing country rising to global entrepreneurial leadership.

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 U.S. firms have served as the template after which firms elsewhere have stylized themselves, 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 re-

[1] This is described in Basu and Weil (1998) and Acemoglu and Zilibotti (2001). Also see Moscona and Sastry (2023, `https://ssrn.com/abstract=3886019`) 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, in our baseline analyses, we define developed market countries as the original members of the Organization of Economic Cooperation and Development, and those that joined through 1980.

[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 U.S.) like sitting in a time machine. Source: `https://shorturl.at/ftFIP`.

sponse 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 U.S. may not be right elsewhere, and those that would have flourished elsewhere may not be suitable in the U.S. Such misalignment may be especially strong between the U.S. 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 U.S., 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, 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]

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

While the EdTech example suggests that China's rise could benefit other emerging economies, there are also several reasons that this may not be the case. For example, investors may not have systematically departed from their historic reliance on U.S. benchmark companies when making investment decisions. Or even if they have, China's economy may be sufficiently different from other emerging economies (e.g., its size and integration), or beholden to political pressures, that business models developed there are not broadly applicable. Finally, it is possible that the best business ideas are not specific to any context and would work well anywhere they emerge, implying that which country serves as the global VC leader does not meaningfully impact patterns of entrepreneurial success around the world.

[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/`.

To answer these questions, we combine several data sources and new empirical measures. First, we compile comprehensive records on venture deals around the world between 2000 and 2021 using PitchBook, a venture capital database designed from its inception to have global coverage. The database includes information about each financing round of all firms — 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 empirical 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 U.S.) as "China-led" sectors.

Third, we seek to to measure the potential "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, link each of these variables to one or more of the macro-sectors in the PitchBook data, and construct an aggregate similarity measure for all countries and macro-sector pairs. This serves as an *ex ante* measure of the economic similarity between China and all other countries in each sector.

Finally,we use Natural Language Processing (NLP) tools to measure similarity in business description across company pairs within each sector. This allows us to examine not just how startups on developing countries mirror the sectors of the U.S. and China, but also the closeness of the business models employed within particular subsegments.

We present three sets of findings. First, as the Chinese venture industry rose in importance, emerging market VC investments grew substantially more in the sectors dominated by China. We begin with a triple difference-in-differences strategy, comparing venture investments in China-led sectors vs. sectors not led by China, before vs. after the acceleration in of Chinese venture investments, and in emerging vs. developed economies. We find that venture investments in China-led sectors increased substantially in developing countries and in China-led sectors, relative to developed countries and relative to the non-China-led sectors. The triple-difference specification includes all two-way fixed effects, making it possible to fully absorb any country-level trends (country-by-year effects), global sector-level trends (sector-by-year effects), or any average differences in the

[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.

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.

We then move to the core empirical strategy and document that the global growth in China-led sectors is driven by country-sector pairs where *ex ante* economic and social data indicate that Chinese technology would be most suitable. We again estimate a triple-difference specification, but instead of comparing developed to developing countries, we look across country-sector pairs where Chinese technology is likely to be more or less suitable. A one standard deviation increase in macro-sectoral suitability is associated with a 192% increase in venture investment deals among China-led sectors in the post-period. These findings are similar even *within* emerging markets.

The results are robust to a range of alternative sample definitions and alternative outcomes (e.g., total investment amount, average investment per deal). We also employ a different identification strategy, where we exploit early and largely idiosyncratic Chinese startup successes as predictors of Chinese sector-level growth. We also show with a series of falsification tests that these results truly capture within-country variation in the suitability of Chinese technology. We re-estimate our regression specification: *(i)* instead of using country-by-sector similarity with China, we employ similarity with all other countries; and *(ii)* instead of the actual country-by-sector similar score with China, we employ that of a randomly selected sector in the same country. In both cases, our baseline estimate is larger than all placebo estimates.

Second, we document that the increase in venture investments in emerging economies is driven by local investors. These new firms have business models that more closely resemble those of their Chinese counterparts, in addition to being in similar sectors. While investors based in the U.S., China, and local venture capital funds all contribute to the rise of venture investments in suitable country-sector pairs, the largest increase is observed among local investors (a one standard deviation increase in suitability leads to a 97.36% increase in deals with local investors). We also show that the new firms in these suitable country-sector pairs are more likely to replicate Chinese business models. In particular, following the rise of China (and only in China-led sectors), we observe a substantial increase in textual similarity between the descriptions of domestic firms and the descriptions of Chinese firms founded during the preceding five years.

Moreover, 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 show that the increased venture investments in China-led sectors generated positive spillovers in emerging markets. We first document the presence of cross-sector spillover effects. Greater venture investments in China-led sectors were accompanied by the emergence of serial entrepreneurs — individuals who begin multiple startups. 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, we show 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.[8] We then document the presence of cross-firm spillovers. Localities with greater pre-existing share of firms in the China-led sectors experienced an increase in the number of new firms established locally after the rise of Chinese VC, further indicating that the rise of China boosted local entrepreneurship ecosystems. This pattern is especially strong in developing countries.

Taken together, our findings suggest that the approach to venture investment based on following U.S. benchmarks might have limited VC growth in developing countries. Companies designed for the U.S. 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, it may have strong (and positive) implications for growth. More broadly, these findings suggest that the growth of new emerging-market centers of research investment, in China or elsewhere, could have large and global productivity impacts. We discuss some of these more speculative consequences of our findings, including the implications for "soft power" and the consequences for China's very recent shifts in venture policy, in the conclusion.

This work is related to three strands of the economics literature. First, there is a substantial body of work on international technology diffusion. Among the relevant works are Barro and Sala-i Martin (1997), Eaton and Kortum (2002), Keller (2002, 2004),

[8]We repeat this analysis focusing on serial *investors* rather than serial entrepreneurs and find very similar, although somewhat less precise, results.

Comin and Hobijn (2010), Comin and Mestieri (2014, 2018), and Giorcelli (2019).[9] Particularly relevant is a subset of this work focusing on how the "appropriateness" of technology may shape technology diffusion and productivity differences (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006; Moscona and Sastry, 2023, `https://ssrn.com/abstract=3886019`). While existing work in this area has highlighted the costs of the concentration of R&D for developing countries, we investigate the benefits of expanding R&D to new markets.

A second strand is the growing body of work on innovation in China, including Holmes, McGrattan and Prescott (2015), Aghion et al. (2015), Fang, Lerner and Wu (2017), Wei, Xie and Zhang (2017), Beraja, Yang and Yuchtman (2023), Chen et al. (2021), and König et al. (2022). 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).

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 strategies. Section 4 documents our main findings that emerging market VC follows China and that this pattern is driven by country-sector pairs where we predict Chinese technology would be most "suitable." Section 5 presents our evidence on mechanisms. Section 6 investigates the broader economic implications of China-led VC growth. Section 7 concludes.

2 China's emergence as a developing country VC leader

Extraordinary rise of venture investment in China One of the most drastic shift 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 U.S. dollars (as are the numbers in this paragraph). Venture investment in China started at 0.27% of the global share (US$ 81 million) in 2001 and remained relatively low (4.39% in share and US$ 3.06 billion in amount) at the eve of its take-off in 2013. This rapidly changed since then: during the 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 2060% increase compared to the 2013 share and level, respectively.

The rise of Chinese venture investment and entrepreneurship in the recent decade

[9] Very little has focused on international knowledge flows from startups with the exception of **?**, which focus on knowledge flows to corporate investors in U.S. startups.

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.

Unprecedented at this stage of development China is unique among nations and unprecedented in history in growing a substantial venture industry at an early stage of development. 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 stage of development 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 (with all numbers presented again in 2011 dollars).

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 0.97% 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 slopping curve is substantially shifted to the left for China. China became a global leader in venture capital at a much lower level of income than any other country.[10]

Following VC leaders as 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

[10]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.

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 model.[11] In the emerging market context, many firms have sought to emulate successful concepts such as e-commerce, mobile payments, and pay now/pay later.[12]

While many of the early efforts to replicate highly successful ventures focused on U.S. 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 U.S. As a result, there does not exist a U.S. benchmark for the elementary and secondary education startup sector that 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.

Recent rise of venture investment in emerging markets Venture investment plays an increasingly important role among firms in the emerging markets. To assess the im-

[11]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`.

[12]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.

portance of venture capital in emerging markets, we follow Lerner and Nanda (2020)'s methodology for the U.S. 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 (Ayyagari et al., 2017; Haltiwanger et al., 2013). We focus on companies that went public between 2003 and 2022, given the decreasing data quality in earlier years. 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 U.S., China, and all other emerging markets. About 10% of the young publicly listed firms in the 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 catching up to that in China, it remains substantially lower to that in the U.S. This could reflect many factors, including the maturity of domestic financial markets. It could also be a result of the fact that the venture investors in emerging markets lack appropriate and successful benchmarks, a mechanism that we investigate explicitly in this paper.

3 Data and measures

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.[13] 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, U.S. 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. 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

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

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 U.S. 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 deals.

One concern is with the quality of these data. Kaplan and Lerner (n.d.) 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.[14] To validate the PitchBook data, we compare our measure of reported Chinese venture capital activities — where data access and definitional issues are likely 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, with hundreds of distinct subsegments. Throughout our analysis, we define sectors as the "subsegments" in the PitchBook

[14] In our conversations with practitioners, many felt that PitchBook was the best database for the purposes of this study. A number of respondents believed that the data had more human auditing and data cleansing than some of its competitors. Others noted that many of the earlier incumbent databases only gradually expanded their coverage to include emerging markets, resulting in a variety of potential selection biases. These conclusions are also broadly consistent with the conclusions of the comparison study of venture capital databases by Retterath and Braun (2020), though it focuses on European transactions.

structure (most detailed level) and define macro-sectors as the "markets" in the PitchBook structure (broadest level). Many of the sectoral categories are extremely narrow, such 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. We then use these data to assign the universe of companies to these 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 companies, or approximately 93.73% of the companies that have venture capital deals tracked by PitchBook, are classified into 266 sectors (three of which only have Chinese and/or American companies). Overall, our baseline categorization is able to achieve a high level of accuracy and recall: when testing on uncontaminated datasets, the average accuracy across sectors is 0.97 and the average recall is 0.78 among sectors that have at least 100 companies.

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 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 U.S. 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 U.S. One such sector is "solutions for students (primary and secondary)," which we described in Section 2 and is marked in red in Figure 2.

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 U.S. companies for 2015-2019 is above the median among all sectors. In addition to the baseline (relative) definition, we also have an absolute definition that considers a sector to be China-led if the total

number of venture investment deals received by that sector in China is greater than that in the U.S. for 2015-2019. These are the sectors with a share greater than 0.5 in Figure 2. By construction, half (129) of the sectors are China-led following the baseline relative definition. A smaller but still substantial number (56) are China-led following our stricter definition, where we require more investment in China in absolute terms.

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 U.S.-led sectors, whereas countries outside of the emerging markets have more companies and larger deal sizes in U.S.-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 country-level socioeconomic and development indicators from the World Bank's World Development Indicators (WDI) database. We extract the value of each indicator for each country c in 2000, and denote these as x_c. We then normalize each characteristic to be in comparable, *z-score* units, and define $\hat{x}_c$ as:

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

Second, we determine which socioeconomic indicators are most relevant to the development of each macro-sector. For this part of the analysis, due to the fineness of the 266 sectors, we focus on the 15 macro-sectors ("markets") that are human-assigned by PitchBook (S_i).[15] For example, school enrollment rates are relevant to the Education Tech macro-sector, and arable land as a percentage of land area is relevant to Agriculture Tech and Food Tech.

Third, we aggregate all characteristics to a measure of "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:

$$M_{cs} = \frac{1}{|\mathcal{S}_i|} \sum_{x \in \mathcal{S}_i} \left(\hat{x}_c - \hat{x}_{China}\right)^2$$

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

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 simply subtracted M_{cs} from its maximum and define this as the "China suitability" of each country-sector pair.

This sectoral China-suitability measure captures intuitive patterns. For example, India's agricultural technology macro-sector is substantially more similar to China in terms of local suitability than that of the U.S. In fact, as shown in Appendix Figure A.5 and Appendix Table A.1, across all 15 macro-sectors, the average similarity with China is higher in developing compared to developed countries. When we analogously construct a measure of similarity with the U.S., however, we find that developed countries are much more similar than developing countries. This is a first indication that Chinese technology may be more useful for developing countries than technologies designed for the U.S.

Not only are there large differences in average similarity with China across countries, there is also substantial variation across sectors within countries. Appendix Figure A.6 plots the distribution of China-suitability and U.S.-suitability for each of the 15 macro-sectors.

3.4 Emulation of business models

In order to capture potential emulation of business models among 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. 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. We calculate pairwise similarity for all companies in a given sector for all sectors. Therefore, we are able to calculate each company's average textual similarity with existing Chinese companies in the same sector.

For example, as previously discussed, Byju's from India and Yuanfudao from China are both in the Edtech macro-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 and other related companies in China. Consistent with this, using the two companies' descriptions, we estimate a high (80.11%) level of

textual similarity between Byju's and Yuanfudao.[16] However, Byju's is not similar to *all* Chinese companies in the same sector. For example, the Chinese company Yundee has a much lower (28.59%) level of textual similarity with Byju's, which makes sense because Yundee's major focus is expanding educational tools for autistic children.[17]

4 Do venture investments follow China?

In this section, we investigate whether the rise of China's venture investments since 2013 has led to changes in venture activities in other emerging economies. We begin in Section 4.1 with comparison across sectors that are China-led and those that are not. We then present, in Section 4.2, our main empirical strategy where we investigate whether the global diffusion of China-led sectors is driven by the potential suitability of Chinese business models and technology.

4.1 Emerging vs. developed countries

We begin by examining the extent to which the rise of China increased venture investments in emerging markets across the board. The Indian primary and secondary education case above suggests this relationship is a real one—but this case may also be an extreme or misleading example. The bulk of venture activity may still follow the U.S. template, either because its initially dominant position in venture capital or because the idiosyncrasies of the Chinese market may deter others from emulating it.

To investigate this pattern systematically, we use a triple difference-in-differences strategy. We compare venture investments in sectors that are led by China with those that are not (which implicitly means they are led by the U.S.), before and after the boom of venture activities in China in 2013, across emerging and developed countries. Specifically, we

[16] 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."

[17] 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."

estimate the following regression model:

$$y_{cst} = \beta\left(ChinaLed_s * Post_t * EM_c\right) + \alpha_{cs} + \gamma_{ct} + \sigma_{st} + \epsilon_{cst}, \quad (1)$$

where c indexes countries, s indexes sectors, and t indexes years. $ChinaLed_s$ is set equal to one if s has above median Chinese deals, $Post_t$ to one for all years after 2012, and EM_c is coded as one if the nation was not in the OECD before the 1980s[18]. The outcome of interest, y_{cst} is the number of deals in the country-sector-year, normalized by the total number of pre-2012 deals in the country.

β is the coefficient of interest. If $\beta > 0$, the regression implies that the rise of Chinese VC led to international growth in the sectors dominated by China, and that this growth took place disproportionately in developing countries.

We control for three sets of fixed effects to account for several potential confounding explanations. 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 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 emerging markets. Finally, $country * sector$ fixed effects control for differences in entrepreneurial specialization by country, as long as these do not sharply change after 2013.

Table 3, columns 1 and 2, reports the results of these regressions. Global growth in investments in China-led sectors appears to follow the rise of the Chinese venture sector. β is positive and significant, whether the regression is unweighted (column 1) or weighted by the global number of deals in the sector (column 2) in order to make sure that the finding is not driven by small or unimportant sectors.

We next break down the triple-difference estimates and report the effect separately for all countries, developing countries, and developed countries. That is, we estimate:

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

separately for each sample. In column 3, we estimate Equation 2 on the global sample, and find a positive and significant coefficient. In columns 4 and 5, we estimate Equation 2 separately for developed and developing countries and find that the global increase

[18]These countries (with the year of membership) 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), United States (1961). Source: `https://www.oecd.org/about/document/ratification-oecd-convention.htm`.

in investment in China-led sectors is entirely driven by the developing countries. The effect for developed countries is small in magnitude and statistically indistinguishable from zero. Thus, 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 addition to the pooled specifications, we also estimate an event study specification, where we include year indicators interacted with either $ChinaLed_s$ (separately for emerging economies and non-emerging economies) or $ChinaLed_s * EM_c$ on the right-hand side of the regression. Figure 3, Panels A and B, present these estimates, respectively. Panel A shows the absence of a pre-trend and the rapid increase in the coefficient on the interaction term in the mid-2010s for emerging markets are readily apparent.

Finally, we plot in Appendix Figure A.7 the trend of venture deal counts among China-led and non-China-led sectors, relative to their corresponding pre-2013 mean levels. VC deals are rising across all sectors in emerging markets, albeit at a noticeably faster pace in the China-led sectors. This indicates that the differential increase in VC investments in China-led sectors does not seem to come at the expense of investment (at least in absolute terms) among other sectors in emerging markets.

4.2 The suitability of Chinese business models

4.2.1 Empirical strategy

The results presented in the previous section suggest that venture investments increased among China-led sectors in emerging economies. While we control for a number of factors that could account for the co-movements in venture investments between China and emerging economies, one may be concerned that global trend in sector-specific investment unrelated to the rise and specialization of China could explain the results.

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 is suitable to 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 similar to China.

Specifically, we estimate the following regression model:

$$y_{cst} = \beta \left(ChinaLed_s * Post_t * ChinaSuitability_{cs} \right) + \alpha_{cs} + \gamma_{ct} + \delta_{st} + \epsilon_{cst}, \tag{3}$$

where the *China suitability* measure, as described in Section 3.3, varies at country×sector

level. As in the previous section, we include a full set of two-way fixed effects.

The coefficient of interest is β. 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. This specification helps rule out the main empirical concern, which was that some sectors grew in emerging markets for reasons unrelated to China's investment dominance. In this specification, presented in Equation 3, this would only be a concern if this emerging market growth happened to also be restricted to country-sector pairs most similar to China. Moreover, Section 4.2.3 presents a series of falsification exercises consistent with a causal interpretation of our estimates.

4.2.2 Results

Table 4, columns 1-2, present the baseline estimates of Equation 3. The estimates of β is positive and statistically distinguishable from zero ($p < 0.01$). A one standard deviation increase in sector-specific suitability is associated with a 180% 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.

In Figure 4, 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 4a conveys: the effect of each decile is small in magnitude and statistically indistinguishable from zero. Figure 4a shows, however, that after 2013, there is a clear positive relationship between decile of the suitability index and venture activity. With one exception, the bars increase moving from left to right. Social and economic similarity to China was a strong determinant of global growth of sectors led by Chinse companies.

Figure 5 explores these dynamics in greater detail. In particular, we include a full set of year indicators interacted with $ChinaLed_s * HighSuitability_c$ or $ChinaLed_s * LowSuitability_c$ on the right-hand side of the regression, where high and low suitability are defined as values of the suitability index in the top or bottom two deciles respectively. The two sets of

country-sector pairs were on very similar trends prior to the rise of China. Starting in 2014 they begin to diverge, with the high-suitability country-sector pairs increasing relative to the excluded group and low-suitability country-sector pairs declining relative to the excluded group. The gap widens through the remainder of the sample period.

Finally, columns 3-4 of Table 4 return to estimates of Equation 1, but estimated it separately for country×sector sets with high vs. low 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 about four times larger when focusing on the top three quartiles of the similarity 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 5. Column 1 of Panel A first replicates the baseline estimate from Table 4. Column 2 shows that the estimates are very similar if we weight the regression by the global number of 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.

Finally, Panel B of Table 5 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 U.S. 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.

4.2.3 Falsification tests

There are two remaining concerns with the interpretation of our estimates of Equation 3 presented in Tables 4 and 5. 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 each other country. We then estimate a series of versions of Equation 3 in which we replace $ChinaSuitability_{cs}$ with the analogous suitability measure for each other country around the world. If our estimates are truly driven by the rise of China and economic similarity to China, we would expect the placebo estimates to be centered around zero and our main coefficient estimate to be in the right tail of the coefficient distribution.

Figure 6a presents the histogram of placebo coefficients in green and our main coefficient estimate from Table 4 with a vertical red line. Reassuringly, the placebo coefficients are centered around zero and our main estimate is by far the largest. These results are consistent with an interpretation of our main results as the sector-specific consequences of the suitability of Chinese business models.

To address the second concern, we again estimate a series of placebo versions of Equation 3, now randomizing the sectoral component of $ChinaSuitability_{cs}$ within each country. That is, 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 3. Figure 6b presents the histogram of these placebo coefficients in green and our main coefficient estimate from Table 4 again as a vertical red line. Our estimate is 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.

4.2.4 Alternative empirical strategy: Early unicorns in China

An alternative empirical strategy is to exploit the emergence of successful companies in China early in the sample period as a shifter of sector-level leadership. Our motivation for this strategy 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, we argue that 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 that there is a degree of randomness in which sectors China's earliest unicorns fell, and which subsequently attracted follow-on investments. 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. Columns 1 and 2 of Table 6 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 6, we repeat the baseline estimates from Tables 3 and 4, 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.

5 Mechanisms

5.1 Mirroring Chinese business models

The findings from the previous section documented 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 business models that were successful in China.

To investigate this hypothesis more directly, we use the methods outlined in Section 3.4 to measure the similarity between each company around the world with Chinese companies founded in the same sector during the preceding five years. Then, for each country-sector pair, we measure the average similarity to recent Chinese companies. We also measure 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 3 with these within-sector measures of companies' similarity to China as the dependent variables.

Table 7 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 are suitable country-sector pairs growing in response to the rise of China, but companies in these sectors are becoming more similar to their Chinese counterparts in the same sector.

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 8 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 9 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 U.S. (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?

To this point, we have focused on the reasons why Chinese businesses might be more economically suited to emerging economies. This has been based on the idea that Chinese entrepreneurs are likely to focus on business models that would work well in China and, as a result, may also be developing business models and technologies with broader applications in emerging markets. However, 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. (2023, `http://davidyyang.com/pdfs/aitrade_draft.pdf`)).

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. Are these political initiatives responsible for the development of the business models that end up diffusing to emerging markets?

To investigate these questions, we developed two proxies for political closeness to China: *(i)* voting similarity on UN resolutions, which captures countries' international political stance;[19] 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.[20]

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 that China is critically dependent upon U.S., 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

[19]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.

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

our baseline analysis.

To understand whether and how politics shapes our baseline results, we estimate versions of our baseline regression (Equation 3), restricting the sample to countries that are either China's friends or enemies, and restricting the sectors to strategic and non-strategic technologies.

Table 10 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 Polity score similarity 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 represents one of the strategic technologies 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, led to large spillovers in 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 3 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 11. We estimate a negative coefficient on both terms—statistically significant in the case of UN voting distance —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" also 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 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 of this substitution 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 12 presents estimates of Equation 3 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 finding 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, `http://www.nber.org/papers/w30604`). The coefficient is again positive and significant.

Together, this evidence suggests that our findings are not driven by firms that fail. Rather, the results suggest the benefits of more "appropriate" investment strategies. 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 the rise of China led to 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:

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

where y^X_{cst} is the number of serial founders (or investors) whose *first* company was in sector s, who became a serial founder (or investor) in year t. We also break down follow-on companies based on the sector(s) that they fall into, and separately estimate the effect on follow-on companies that fall into sector grouping X, where

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

Table 13 reports estimates of Equation 4, focusing on entrepreneurs. Column 1 shows that the rise of China has led to a larger group of serial entrepreneurs in other emerging markets. There are many more serial founders among entrepreneurs whose first company was in one of the China-led sectors and in "suitable" country-sector pairs.

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 a sectors that are not led by China. The coefficient is again positive and significant.

These findings suggest that while serial entrepreneurs are most likely to emerge from China-led sectors, they use their reputational capital and knowledge to explore 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 investigate serial *investors*. Table 14 follows the same structure as Table 13,

except all outcomes focus on serial investors instead 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, 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 locally-focused businesses in other sectors.

6.3 Local firm dynamics and geographic spillovers

So far, the results have focused on country-by-sector-level variation in the 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 entrepreneurial activity.

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 startups 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 startup 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 city i and year t.[21]

We first restrict attention to cities in emerging economies. In column 1 of Table 15, the outcome variable is the (inverse hyperbolic since transformation of the) number of companies founded. We estimate that γ is positive and significant. In columns 2 and 3, the outcome is the number of deals and total deal value respectively. We again estimate positive and slightly large values for γ.

In columns 4 and 5, we separately estimate the effect on companies in one of the China-led sectors and companies that are not. The results from columns 1-3 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.

[21] We geo-locate the headquarters of all companies in the PitchBook database using SimpleMaps data, linking each to the nearest populated city from Natural Earth database. We restrict attention for our analysis to cities with at least 12 (the median value) 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 481 cities in 93 countries.

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 about two-thirds the magnitude 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.

Finally, in column 6, we use the full sample of countries and investigate whether, as in the sector-level analysis, the positive effect of the rise of China on local entrepreneurship is larger in emerging markets. 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 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.

7 Conclusion

The paper seeks to understand the implications of the rise of the Chinese venture capital industry — an unprecedented case in the developing world — for 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 U.S.) has facilitated the funding of more 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, he entrepreneurial success of the Chinese models may also lead to relative more credibility for "the Chinese model," at the expense of U.S. 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 economic footprint would enjoy otherwise (see the discussion in Senor and Singer (2009)). Understanding the consequences of Chinese entrepreneurial success and its diffusion for "soft power" is an important, if difficult to address, question.

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 tutoring and 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 to government objectives.[22] 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.

Finally, our study is a first step towards systematically evaluating the benefits and drawbacks of a U.S.-led entrepreneurship system, especially from the perspective of developing countries. It provides some evidence about modifying the system that so that at once maintains the economies of scale from a high concentration of entrepreneurship 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.

[22]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.

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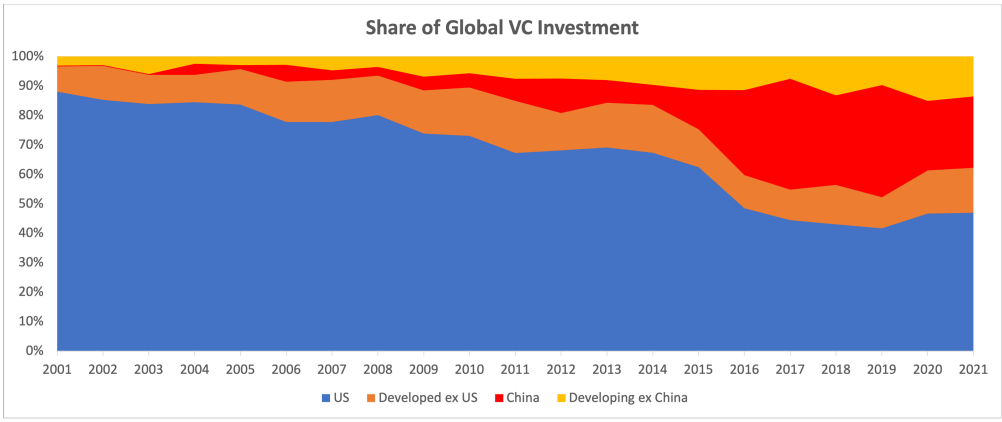
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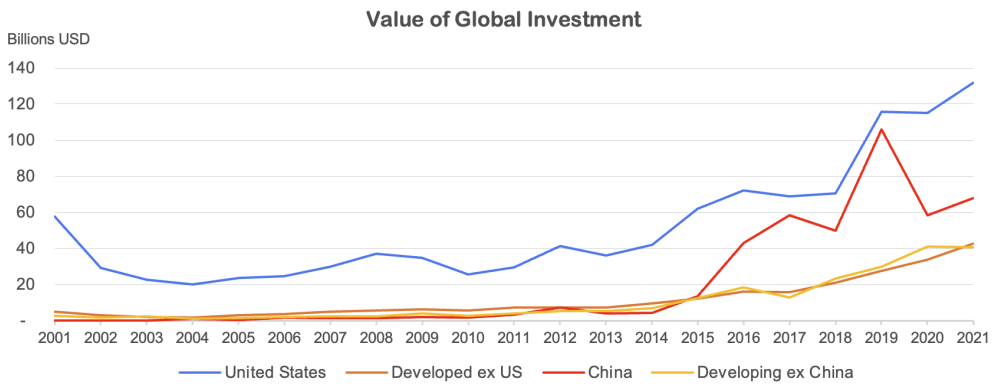
Figures

Figure 1: Venture Investment Overview

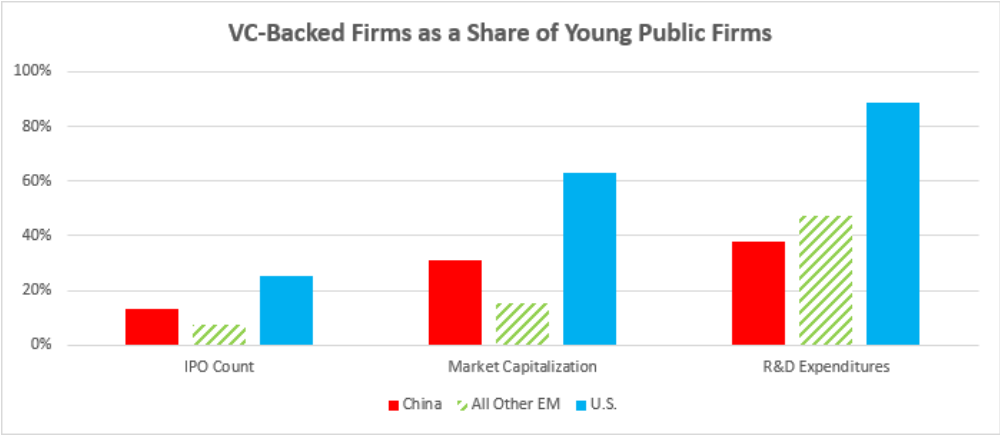
(a)



(b)

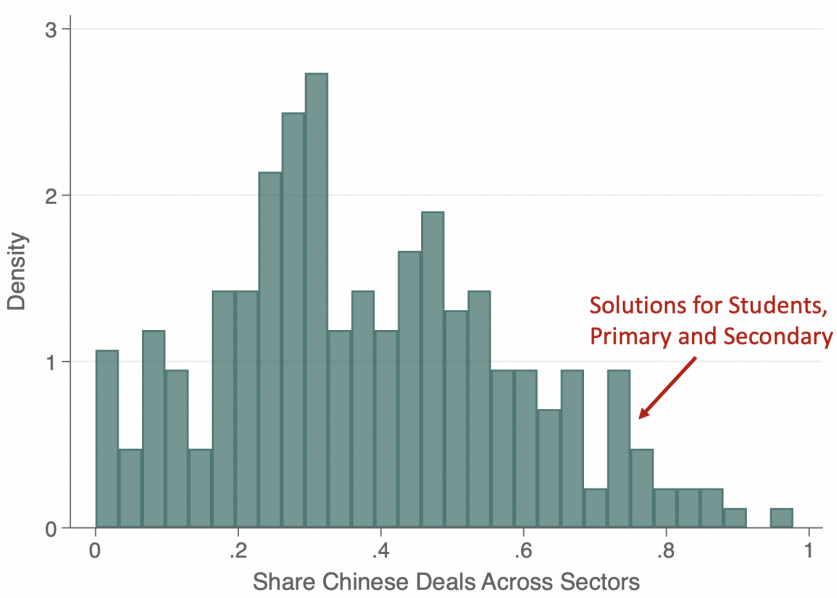


(c)



Note: Figure 1a shows the changing mixture of venture capital investments worldwide. Figure 1b displays the value of venture capital investment worldwide in billions of 2011 dollars. Figure 1c presents VC-backed firms' share in global markets. The sourcing of this figure is discussed in Appendix A.

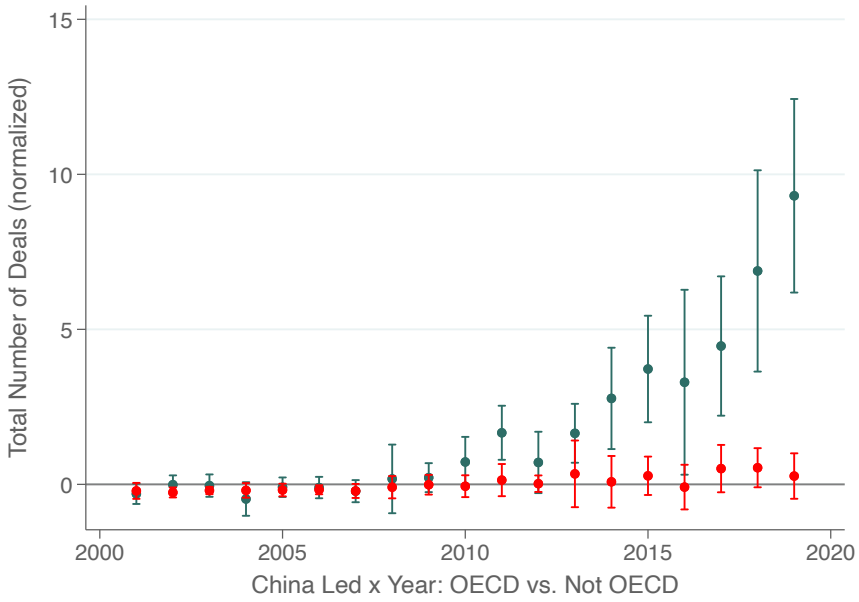
Figure 2: China's Share of Venture Deals Across Sectors



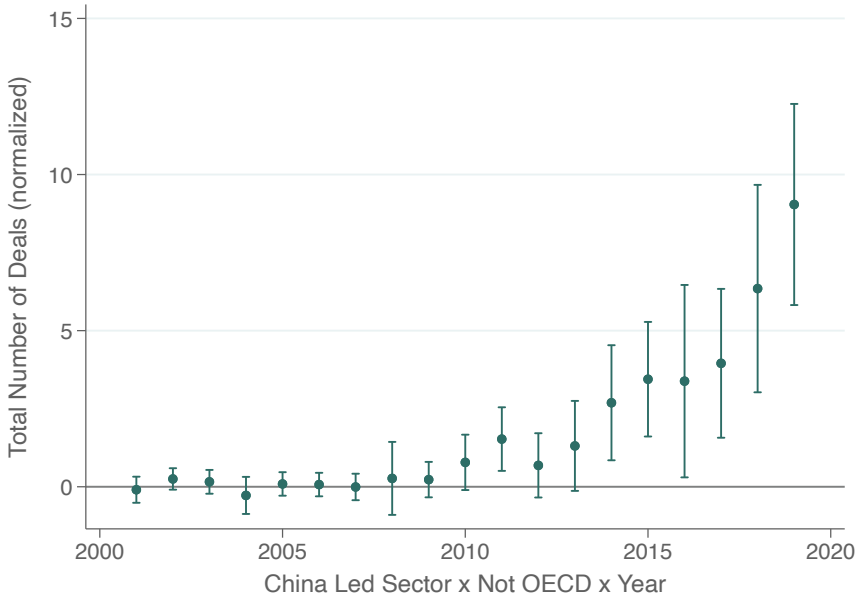
Note: This figure plots a histogram of the share of all venture deals in each sector from 2015-2019 that took place in China. The value for the sector "Solutions for Students, Primary and Secondary" is marked in red.

Figure 3: Dynamic Effects: EM Investments Follow China

(a) Double-Difference Estimates



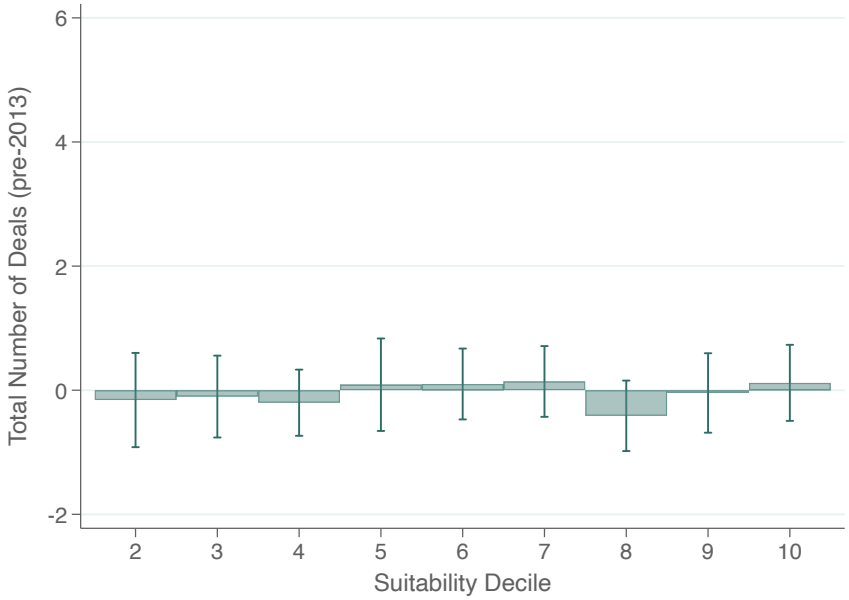
(b) Triple-Difference Estimates



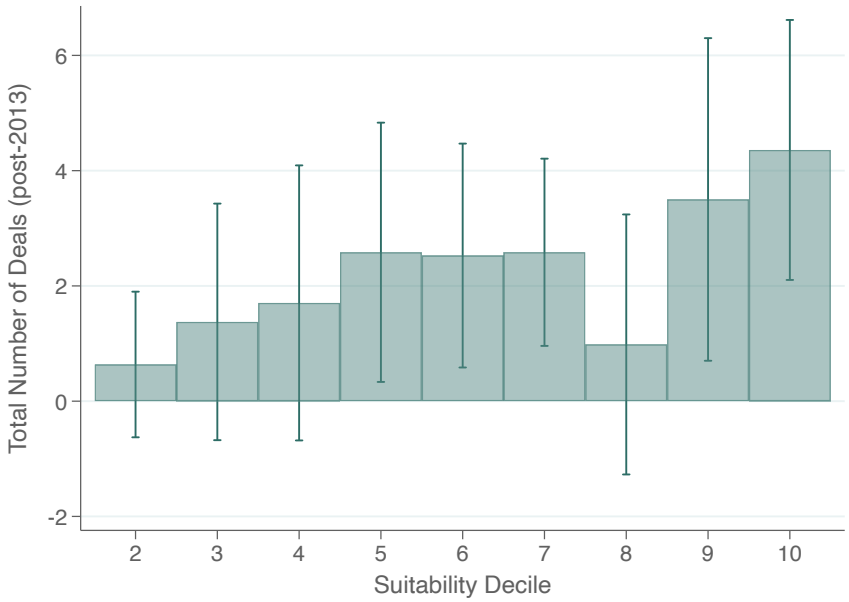
Note: Figure 3a shows estimates of year indicators interacted with $ChinaLed_s$, separately for countries in the OECD by 1980 (red) and countries outside the OECD in 1980 (green). Figure 3b displays triple-difference estimates of year indicators interacted with $ChinaLed_s * EM_c$. The year 2000 is the excluded category in both figures. Standard errors are clustered by country and 90% confidence intervals are reported.

Figure 4: Suitability Effects by Decile: Pre vs. Post Peirod

(a) Pre-period (before 2013)

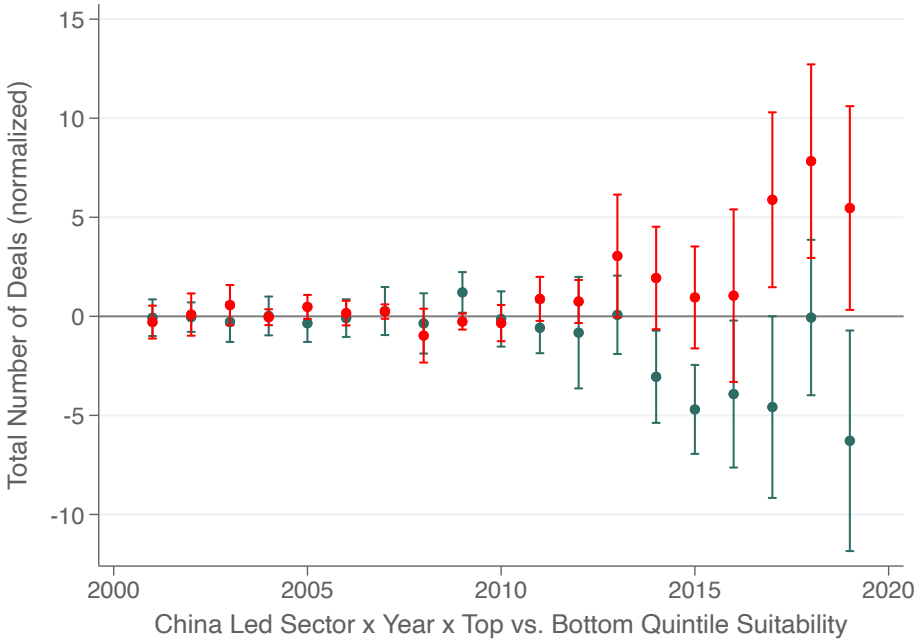


(b) Post-period (after 2013)



Note: Figure 4a 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 4b 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.

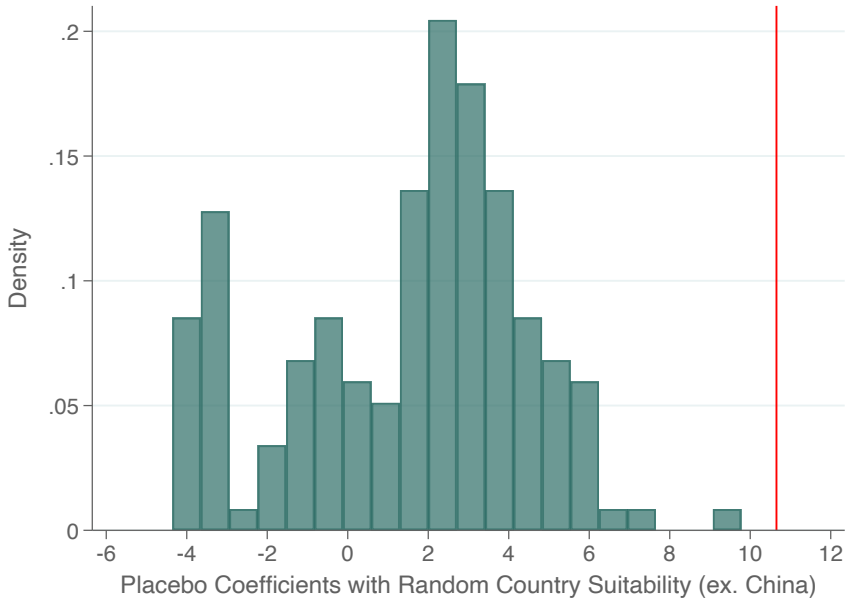
Figure 5: Suitability and Venture Activity: Dynamics



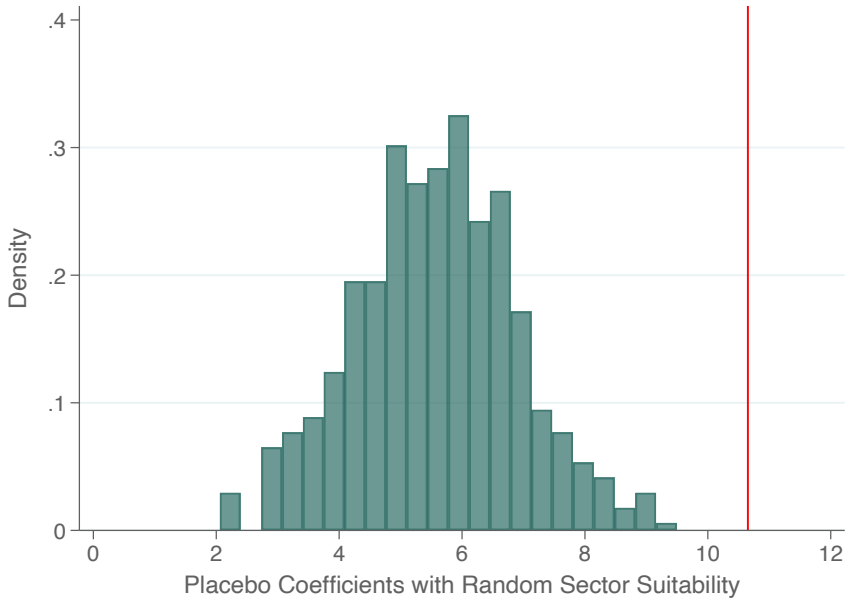
Note: This figure shows estimates of year indicators interacted with $ChinaLed_s * HighSuitability_{cs}$ (red) where $HighSuitability_{cs}$ is an indicator that equals one if the suitability score is in the top two deciles, and estimates of year indicators interacted with $ChinaLed_s * LowSuitability_{cs}$ (green) where $LowSuitability_{cs}$ is an indicator that equals one if the suitability score is in the bottom two deciles. Standard errors are clustered by country and 90% confidence intervals are reported.

Figure 6: Falsification Tests

(a) Random Country Placebo



(b) Random Sector Placebo



Note: Figure 6a reports a histogram of coefficient estimates from a series of estimates of Equation 3 in which $ChinaSuitability_{cs}$ is replaced with an analogous suitabiliy measure for each other country. Our main estimate of β from Equation 3 is displayed with a red vertical line. Figure 6b also reports a histogram of coefficient estimates from a series of estimates of Equation 3 in which the sector component of $ChinaSuitability_{cs}$ is drawn at random each time. Again, our main estimate of β from Equation 3 is displayed with a red vertical line.

Tables

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

Country	"Emerge 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 shares and innovation measures for selected countries when they are at a similar level in terms of GDP per capita with China in 2015 (all GDP values in 2011 US dollars). The sourcing of this figure is discussed in Appendix A.

Table 2: Summary Statistics

Panel A: VC Deal Statistics

	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 deals	44.12%	49.19%	51.86%	30.38%	37.17%

Panel B1: Sector Prediction Statistics

	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 sectors	3.51	3.00	1.47	72943

Panel B2: China-Led Sectors Statistics

	China-led Sectors	US-led Sectors
Number of companies	136,908	134,715
Number of companies (other EM)	19,715	15,110
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 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 timespan for all panels is 2000-2019. Panel A reports summary statistics on venture capital (VC) deals extracted from Pitchbook. All deal size information is nominal US dollars. Panel B1 reports summary statistics on sector predictions. Panel B2 reports summary statistics on China-led sectors and US-led sectors. A sector is defined to be China-led if the ratio of the number of VC deals received by Chinese companies relative to that of the U.S. for 2015-2019 is above the median among all sectors. Similarly, US-led sectors are sectors that have below-median of the aforementioned ratio. The unit of observation in Panel B2 is company-sector, so a China-led sector will have one more company as long as one of the company's predicted sectors is China-led.

Table 3: Rise of China Increases Emerging Market Entrepreneurship

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

Notes: The unit of observation is a country-sector-year. EM countries are defined as countries not included in the OECD as of 1980. The dependent variable is normalized by dividing the number of deals in the country-sector-year by the total number of pre-period deals in the country. In column 2, the regression is weighted by the total, global number of deals in the sector during the pre-period. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 4: Suitability of Chinese Technology Increases Entrepreneurship

	Dependent Variable: Number of Deals (Normalized)			
	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Bottom Quartile Suitability	Top Quartiles Suitability
China-Led Sector × Post × China Suitability	10.652***	9.990**		
	(3.739)	(3.888)		
China-Led Sector × Post × EM			1.256	4.907***
			(1.057)	(0.995)
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	547040	547040	126160	473480
Mean of Dep. Var	3.616	3.616	2.571	3.851
SD of Dep. Var	45.076	45.076	27.852	49.509

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 5: 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	10.652***	13.461***	0.130**	0.234**	0.324*
	(3.739)	(4.802)	(0.057)	(0.107)	(0.163)
Panel B: Strict China-led measure					
China-Led Sector × Post × China Suitability	14.217***	18.519***	0.173***	0.350***	0.618***
	(4.298)	(5.819)	(0.039)	(0.103)	(0.203)
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	35507
Mean of Dep. Var	3.616	4.908	0.137	0.186	0.927
SD of Dep. Var	45.076	53.061	0.508	0.806	1.479

Notes: This table reports the robustness of main results. The unit of observation is a country-sector-year. Panel A presents results using our baseline China-led 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 presents using strict China-led measures, where a sector is defined as China-led if the number of deals received by Chinese companies are strictly higher than US companies for the same period. Column 1 repeats our baseline. Column 2 weights the regression by total deals in the sector. Column 3 uses asinh deals as the outcome. Column 4 using asinh deal size as the outcome variable. Column 5 uses log of average size per deal as the outcome. All deal size information is nominal US dollars. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 6: 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			1.169***			
			(0.400)			
Large/early deals (100m) × Post × EM				2.049***		
				(0.645)		
Large/early (50m) deals × Post × China Suitability					6.458***	
					(2.061)	
Large/early (100m) deals × Post × China Suitability						10.446***
						(3.330)
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	547040	547040
Mean of Dep. Var	0.490	0.490	3.582	3.582	3.616	3.616
SD of Dep. Var	0.501	0.501	45.814	45.814	45.076	45.076

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 nominal US dollars. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 7: Increasing Business Model Similarity to China

	Text similarity to existing Chinese companies in the sector	
	(1) Mean Similarity	(2) 90th Percentile Similarity
China-Led Sector × Post × China Suitability	0.016**	0.022***
	(0.007)	(0.007)
Sector × Country Fixed Effects	Yes	Yes
Country × Year Fixed Effects	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes
Number of Obs	42516	42516
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 8: 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	6.804***	3.848**
	(2.545)	(1.580)
Sector × Country Fixed Effects	Yes	Yes
Country × Year Fixed Effects	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes
Number of Obs	547040	547040
Mean of Dep. Var	2.792	0.824
SD of Dep. Var	39.517	18.016

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: 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	1.447	1.193	5.409**
	(1.711)	(0.736)	(2.097)
Sector × Country Fixed Effects	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes
Number of Obs	547040	547040	547040
Mean of Dep. Var	0.810	0.080	1.733
SD of Dep. Var	19.591	4.170	26.697

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 10: Effect of Political Alignment

	Dependent Variable: Number of Deals (Normalized)					
	(1) Top Quantile UN Vote Similarity	(2) Bottom Quantile UN Vote Similarity	(3) Top Quantile Polity Score Similarity	(4) Botom Quantile Polity Score Similarity	(5) Govt Prioitized Sectors	(6) Not Prioitized Sectors
China-Led Sector	14.972**	10.055**	14.457**	9.962***	3.238	12.778***
× Post	(6.928)	(4.141)	(6.971)	(3.635)	(3.456)	(4.641)
× China Suitability						
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	135708	409491	118613	380824	172640	374400
Mean of Dep. Var	4.603	3.304	3.350	3.130	4.672	3.129
SD of Dep. Var	54.566	41.558	46.049	40.832	51.889	41.551

Notes: Columns 1-2 report the differential effects for countries that have top quartile and bottom quartile UN vote similarity with China. Columns 3-4 report the differential effect for countries that have top quartile and bottom quartile polity score similarity with China. Columns 5-6 report the differential effect for sectors that are part of "Made In China 2025" and "China's Strangleholds Technologies", two sets of sectors that are prioritized by the Chinese government. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 11: Results after Controlling for Political Alignment

	Dependent Variable: Number of Deals (Normalized)			
	(1)	(2)	(3)	(4)
China-Led Sector × Post × China Suitability	10.652***	11.313***	10.057***	10.769***
	(3.739)	(3.482)	(3.617)	(3.404)
China-Led Sector × Post × Polity Score Mismatch with China		-0.134		-0.071
		(0.081)		(0.087)
China-Led Sector × Post × UN Voting Mismatch with China			-1.749***	-1.293**
			(0.657)	(0.644)
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	547040	499963	546251	499174
Mean of Dep. Var	3.616	3.179	3.621	3.183
SD of Dep. Var	45.076	42.107	45.108	42.140

Notes: This table adds additional political controls to the baseline results. Polity score mismatch with China denotes the distance between a country's polity score wit China's polity score. UN Voting mismatch with China denotes the distance between a country's UN voting history with China's. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 12: 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	0.506	1.612**	8.533***
	(1.038)	(0.745)	(2.889)
Sector × Country Fixed Effects	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes
Number of Obs	547040	547040	547040
Mean of Dep. Var	0.506	0.501	2.609
SD of Dep. Var	16.060	13.869	38.324

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 13: 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 Sector	0.022**	0.005	0.017**	0.009*	0.014**	0.006	0.010**	0.007*
× Post	(0.011)	(0.004)	(0.008)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)
× China Suitability								
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	547040	547040	547040	547040	547040	547040	547040	547040
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	0.086	0.050	0.077	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 "only in CL sectors" if their companies only fall wihin the China-led sectors from our main analysis, they are "any non-CL sectors" if at least one of their companies falls outside the China-led sectors from our main analysis, and they are "only non-CL sectors" if all of their companies fall ouside the China-led sectors fom our main analysis. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 14: Serial Investors

	Number of Serial Investors				Serial Investor Indicator			
	(1) All	(2) Only CL Sectors	(3) Any non-CL Sectors	(4) Only non-CL Sectors	(5) All	(6) Only CL Sectors	(7) Any non-CL Sectors	(8) Only non-CL Sectors
China-Led Sector	0.120	0.057	0.063	0.033**	0.010	0.007	0.016	0.015**
× Post	(0.089)	(0.047)	(0.045)	(0.015)	(0.018)	(0.020)	(0.011)	(0.006)
× China Suitability								
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	547040	547040	547040	547040	547040	547040	547040	547040
Mean of Dep. Var	0.052	0.017	0.034	0.013	0.029	0.013	0.021	0.010
SD of Dep. Var	0.455	0.186	0.329	0.151	0.168	0.114	0.144	0.097

Notes: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. Investor are "only in CL sectors" if their companies only fall wihin the China-led sectors from our main analysis, they are "any non-CL sectors" if at least one of their companies falls outside the China-led sectors from our main analysis, and they are "only non-CL sectors" if all of their companies fall ouside the China-led sectors fom our main analysis. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 15: City-level analysis

	(1) (asinh) Number of Companies	(2) (asinh) Number of Deals	(3) (asinh) Total Deal Size	(4) (asinh) Number of Companies (any CL)	(5) (asinh) Number of Companies (none CL)	(6) (asinh) Number of Companies
Share China-Led	1.064***	1.727**	1.977**	0.870***	0.564**	0.077
× Post	(0.367)	(0.667)	(0.926)	(0.317)	(0.240)	(0.163)
Share China-Led						0.969**
× Post × EM						(0.398)
City × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	-
Year × EM FE	-	-	-	-	-	Yes
Number of Obs	2304	2304	2304	2304	2304	8978
Mean of Dep. Var	1.086	2.017	2.533	0.978	0.378	1.070
SD of Dep. Var	1.309	1.611	2.656	1.245	0.746	1.229

Notes: The unit of observation is a city-year. "Any CL" denotes companies that have at least one predicted China-led sectors. "none CL" denotes companies that have no predicted China-led sector. The first five columns are for EM countries only. EM countries are defined as countries not included in the OECD as of 1980. All deal size information is nominal US dollars. Standard errors are clustered by 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 time series of venture capital data are two-fold:

- The inconsistencies in measuring venture capital investment activity across data providers: for instance, are the investments classified by the nationality of the fund or the portfolio company, where the line between venture capital and growth investments are drawn, are 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 severely 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, earlier periods than 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 Refinitiv (the Thomson Reuts/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 U.S. 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 U.S. 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 emerging market initial public offerings using Capital IQ, from which we also obtain data on their market capitalization as of mid-August (emerging markets) or early September (U.S.) 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 again 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.

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 U.S. 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 U.S. 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 U.S. 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 inconsistent with the UNESCO-originated investments. For example, in 2011 the World Bank data indicates that Australia the proportion of GDP on R&D was 2.25% while the OECD data suggests this is 1.19%.

  We have (at least in theory), all VC and publications, 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 2 or more years). We assume that firms did R&D in the years where there were no surveys. We impute missing years as follows:

  - If we have R&D in year x and year $x + y$ where $y \leq 5$, we assign to each intermediate year $x + t$ the following amount: $R\&D_{x+t} = R\&D_x + (t/y) *$

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

$(R\&D_{x+y} - R\&Dx)$. For instance, if there is one missing year, 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 U.S. 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 U.S. 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 U.S. dollar series) by population, and then (b) converting from 2017 to 2011 U.S. 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 U.S. 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] :

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

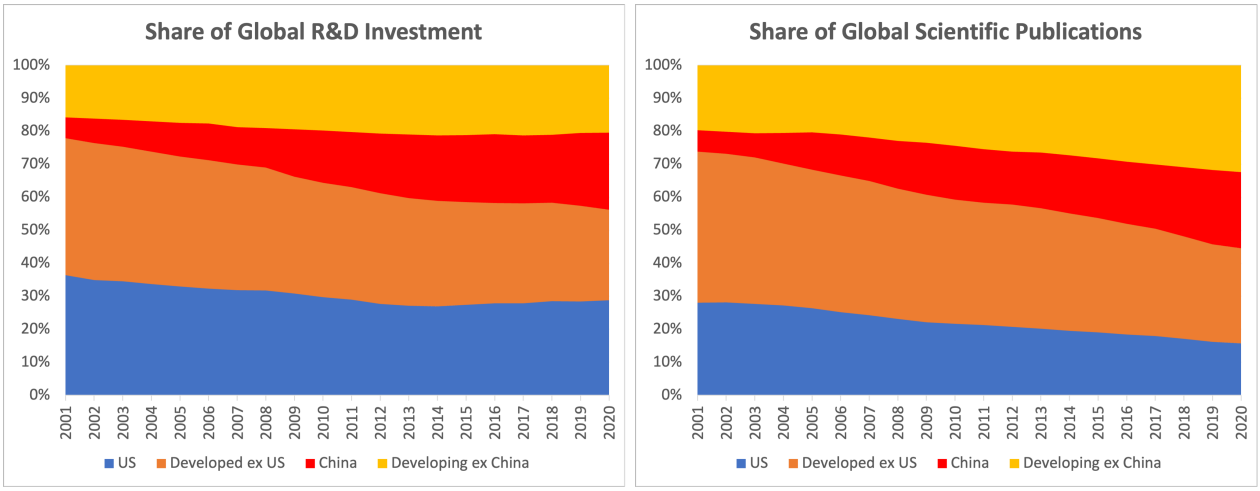
We also compare our measure of reported Chinese VC activity with that reported in two commercial Chinese databases, Zero2IPO and the China Venture Institute. We were motivated to undertake the comparison for two reasons. First, China likely to be setting where data access issues and definitional issues are most severe: e.g., due to role of public sector and SOE funding (Chen, 2022). In addition, Chinese data services use different methodologies, with much greater reliance on government sources. We find the PitchBook data, as depicted in Figure A.4 lies generally between the other two estimates. The results are also consistent with earlier findings of downward bias in Zero2IPO data (Fei, 2018; Li, 2022).

[2]All other currencies converted into U.S. 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 U.S. dollars using the GDP deflator series in the Economic Report of the President (https://www.whitehouse.gov/wp-content/uploads/2023/03/ERP-2023.pdf).

Appendix C Additional Figures and Tables

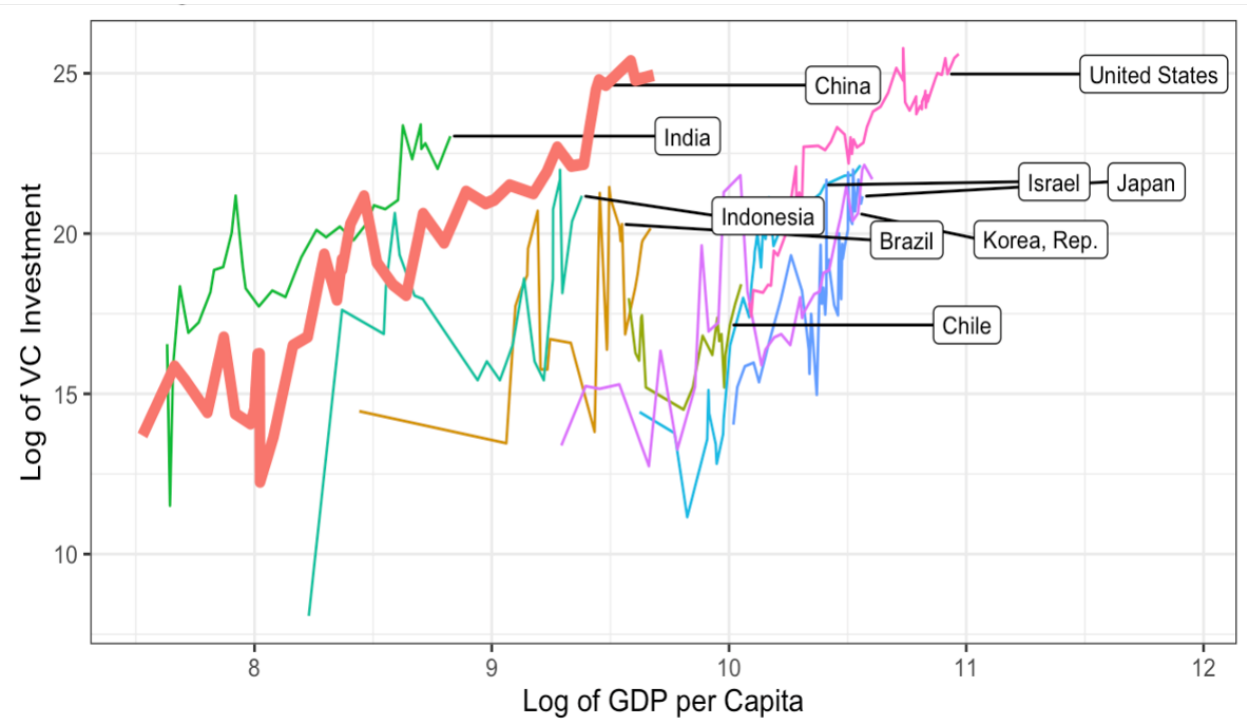
Figure A.1: Global Innovation Overview

(a) (b)



Note: Figure A.1a shows the changing mixture of global R&D investment. Figure A.1b displays the changing mixture of scientific publications. Values are adjusted using 2011 US dollars. The sourcing of this figure is discussed in Appendix A.

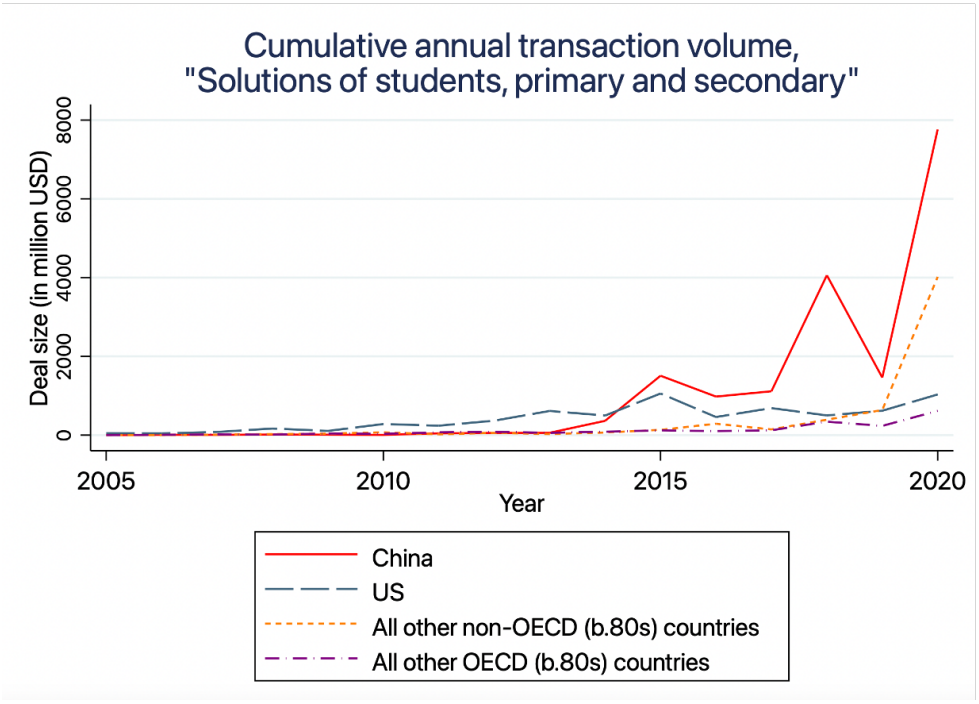
Figure A.2: Venture Investment and GDP Per Capita



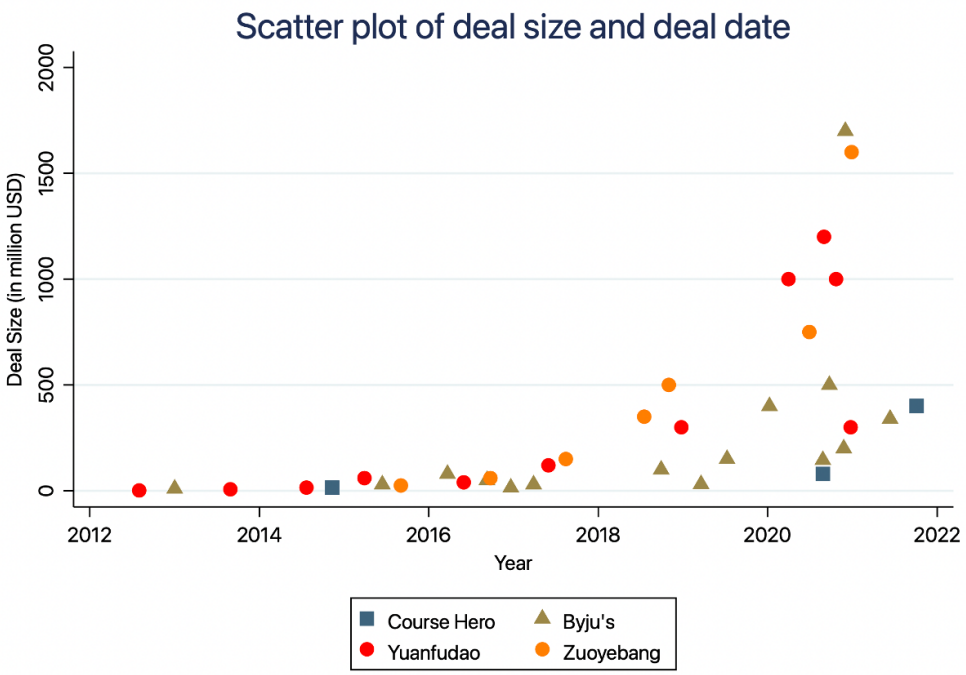
Note: This figure shows countries' growth in terms of GDP per capita and their venture investment. The sourcing of this figure is discussed in Appendix A.

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

(a)

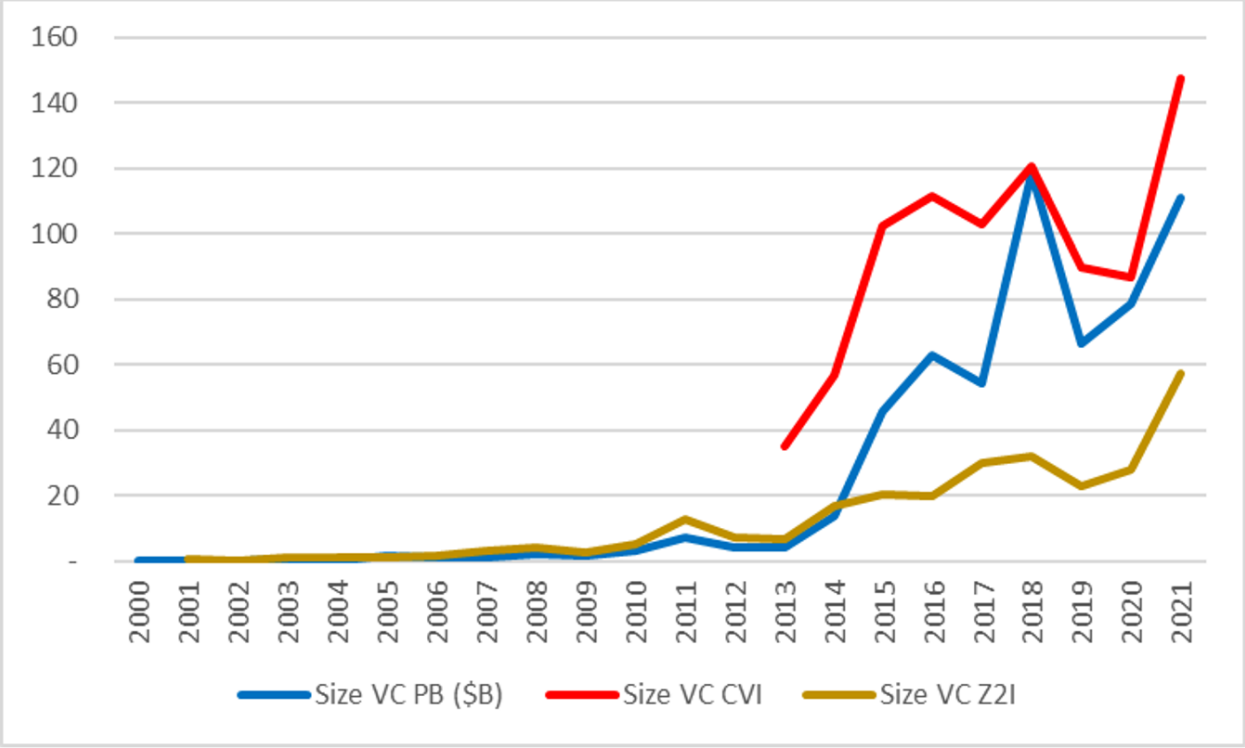


(b)



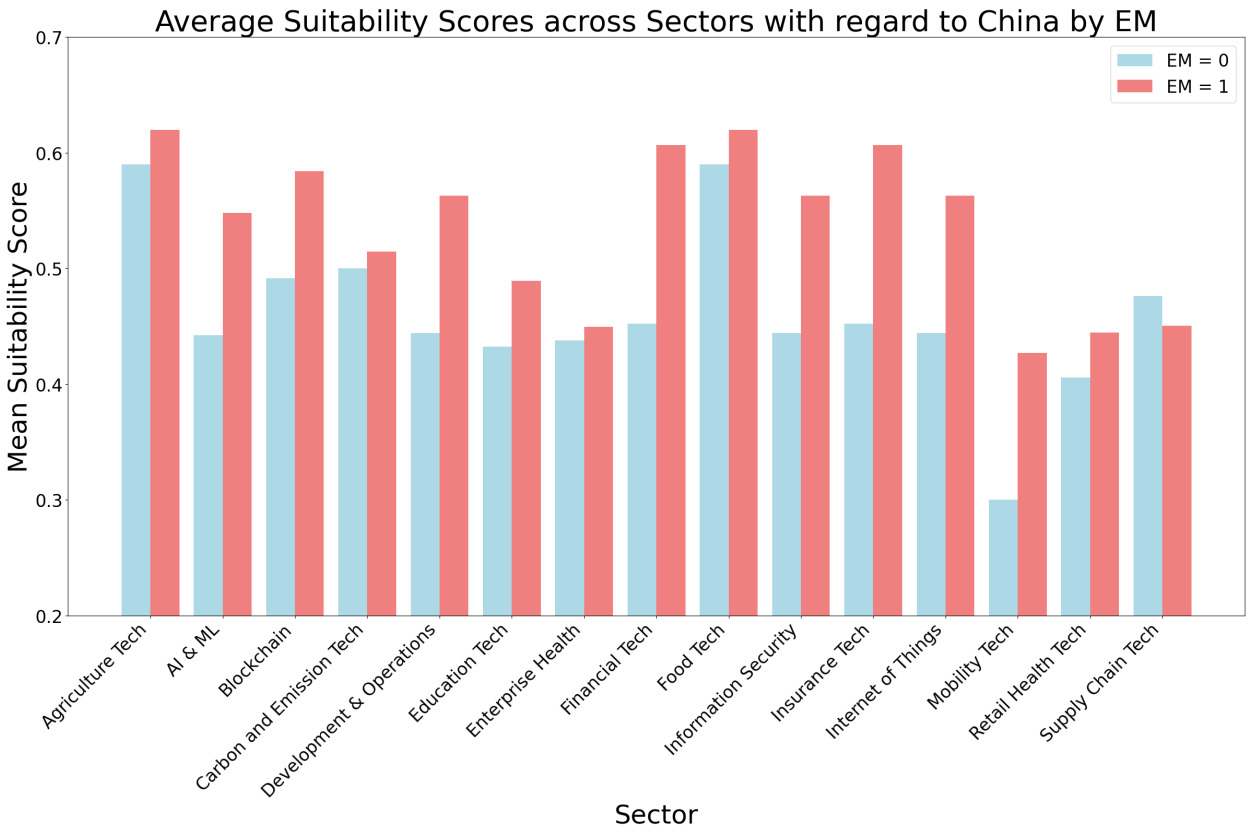
Note: Figure A.3b shows all funding deals for major companies in EdTech-Solution for Primary and Secondary Students sector, where each dot represents a deal. Figure A.3a displays the cumulative deal size for China, U.S., all other emerging countries (countries that didn't join OECD or joined OECD after 1980), and all other developed countries (countries that joined OECD before 1980).

Figure A.4: Cross Validation of Data



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

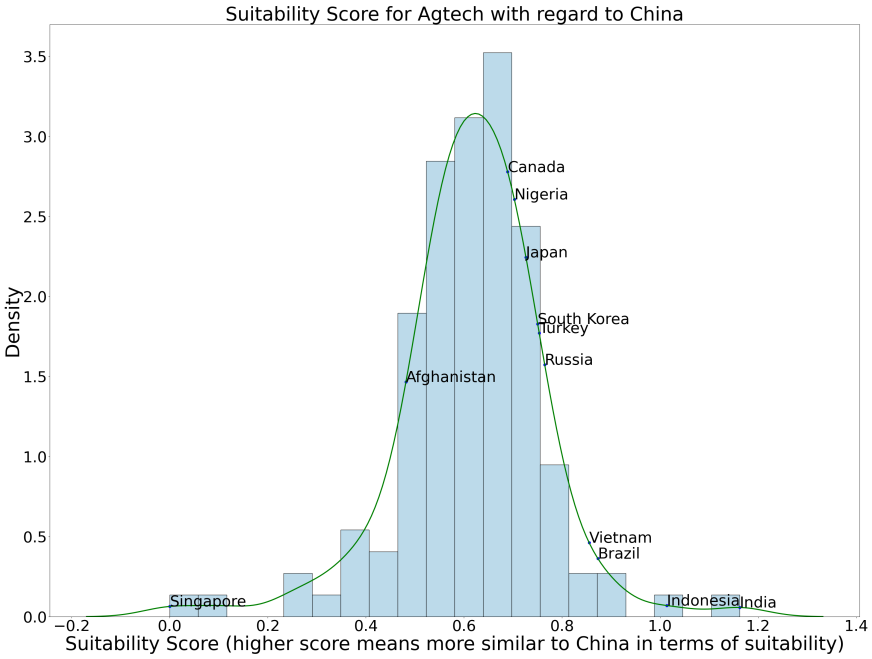
Figure A.5



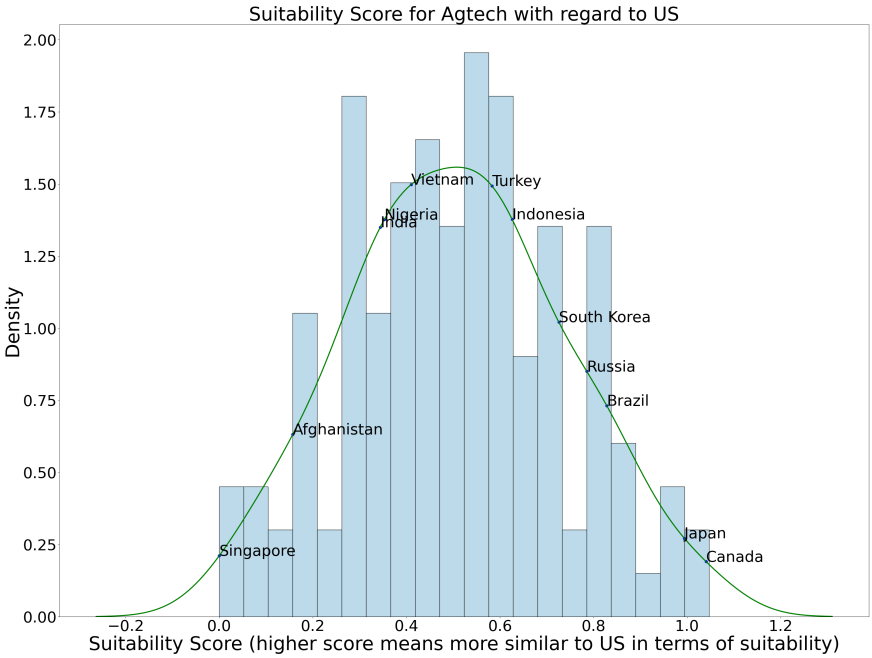
Note: This figure shows average suitability scores with respect to China for the 15 macro-sectors among EM countries and non-EM countries. A higher number denotes higher suitability similarities compared with China. EM countries are defined as countries that did not join the OECD before 1980.

Figure A.6: Within Agricultural Tech Macro-Sector Suitability Variation

(a)

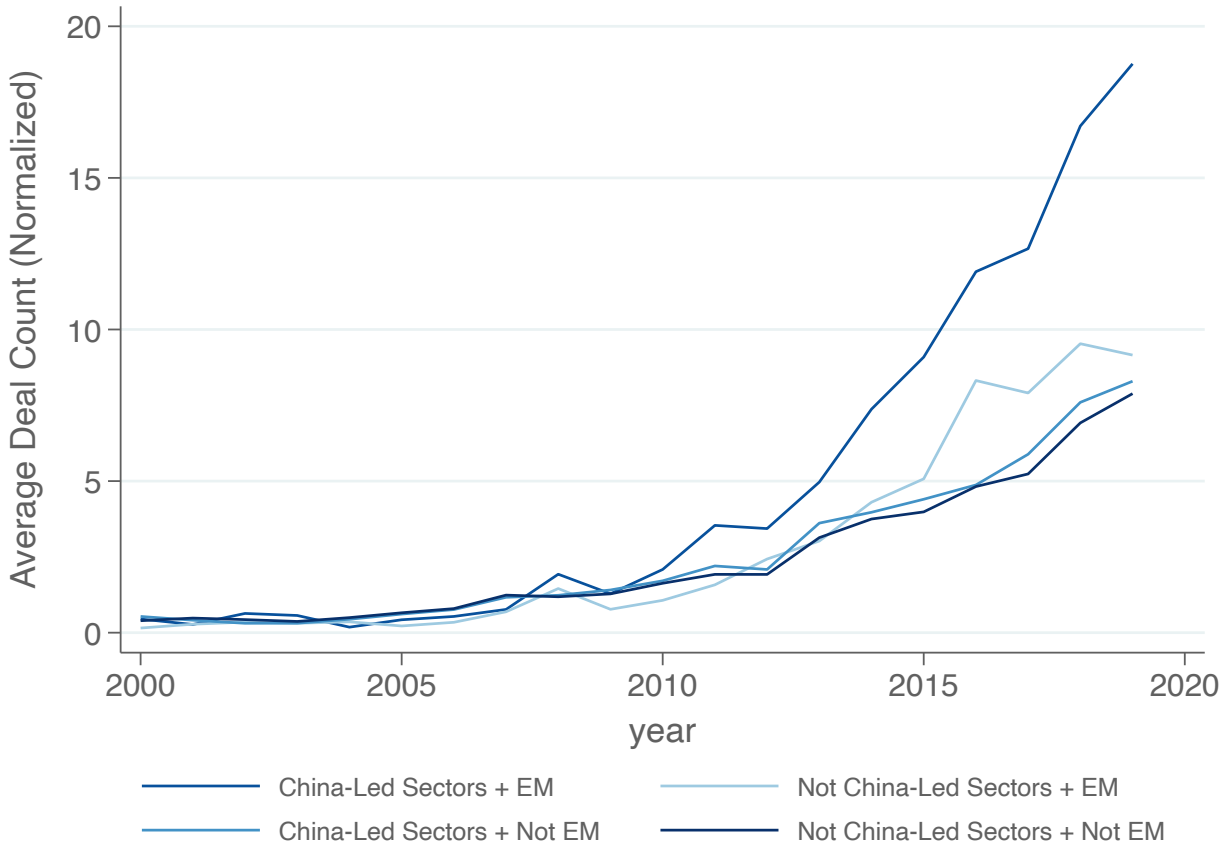


(b)



Note: This figure shows histogram plots and kdensity plots suitability similarity with China and US for macro-sectors. A higher number denotes higher suitability similarity with China or U.S. Selected countries' suitability similarity are plotted on the kdensity plot.

Figure A.7: Trend of venture investment deal count



Note: 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.

Table A.1: Summary Statistics

Marketmap	Suitability Score EM China	Suitability Score non-EM China	EM Premium China	Suitability Score EM US	Suitability Score non-EM US	EM Premium US
AI ML	0.59	0.48	0.11	0.50	1.01	-0.51
AgTech	0.75	0.72	0.03	1.01	1.39	-0.39
Blockchain	0.59	0.49	0.09	0.85	1.35	-0.49
Carbon and Emissions	0.68	0.66	0.01	0.37	0.82	-0.45
DevOps	0.60	0.48	0.12	0.52	1.02	-0.50
EdTech	0.90	0.85	0.06	1.14	1.55	-0.41
Enterprise Health	0.73	0.72	0.01	1.07	1.59	-0.52
Fintech	0.74	0.58	0.15	1.03	1.54	-0.50
FoodTech	0.75	0.72	0.03	1.01	1.39	-0.39
InfoSec	0.60	0.48	0.12	0.52	1.02	-0.50
Insurtech	0.74	0.58	0.15	1.03	1.54	-0.50
IoT	0.60	0.48	0.12	0.52	1.02	-0.50
MobilityTech	0.70	0.57	0.13	0.55	1.05	-0.50
Retail HealthTech	0.83	0.79	0.04	1.25	1.75	-0.51
Supply Chain Tech	0.55	0.57	-0.03	0.63	1.10	-0.47

Notes: This table presents the suitability measures for EM and non-EM. Columns 1 and 2 are average suitability similarity with respect to China, and columns 4 and 5 are average suitability similarity with respect to US. EM premium is defined as the difference between EM and non-EM countries for a given benchmark.

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