Supplementary Appendix

Additional Material for "The Rise and Fall of Great Technologies and Powers"

This online appendix provides additional information about the article's methodology, including case selection and the reasoning for choosing which technologies to track in each case. I also include extended discussions of the first industrial revolution (IR-1) and third industrial revolution (IR-3) cases. Lastly, I present more evidence demonstrating the application of GPT diffusion theory to present-day U.S.-China technological competition.

Methodology: Case Selection

The population of cases includes four types of cases based on whether they score positively or negatively on the cause and outcome (Supplementary Table 1).[1] For example, the Dutch Republic surpassed Portugal as the dominant economic leader (outcome-present) in the early 17th century, but there were not many significant technological innovations during the period (cause-absent). I avoid selecting cases like the Dutch Republic-Portugal power transition because cases where the cause is absent are not helpful for tracing mechanisms. Instead, I prioritize typical cases, where the cause and outcome are clearly present, for building and testing theories of mechanisms.[2]

Supplementary Table 1: A Typology of Cases

	Outcome absent (-)	Outcome present (+)
Cause absent (-)	*irrelevant* Dutch Republic (mid-17th century)	*deviant coverage case* Portugal-Dutch Republic transition (early 17th century)
Cause present (+)	*deviant consistency case* Third industrial revolution	*typical case* First industrial revolution; second industrial revolution

Cause = technological revolution; outcome = economic power transition; shaded = selected.

Therefore, the IR-1 and IR-2 serve as the two foundational cases in my study. Both revolutions brought significant technological advances (cause-present) that were linked to the rise of new industrial powers (outcome-present). The IR-1 and IR-2 were the clear-cut choices among a limited number of typical cases, since a shift in the predominant economic power of the international system, my outcome of interest, is a relatively rare occurrence. Other who study the rise and fall of great powers reach back further in the past for possible cases. Based on Modelski and Thompson's scheme, I considered including shifts in economic leadership from Genoa (1290-1381) to Venice

[1] Based on terminology from Beach and Pedersen 2019, 96-97.
[2] Beach and Pedersen 2019, 97-98; Goertz 2017.

(1381-1494) to Portugal (1517-1580) and to the Dutch Republic (1609-1713).[3] Ultimately, I coded all these cases as ones where the cause of interest was not present, as these all occurred before the industrial revolution marked a fundamental shift in the extent to which technological changes affected the productive power of nations.[4]

To supplement the typical cases, I also study the deviant case of Japan's challenge to American technological leadership in the IR-3. Useful for disconfirming causal mechanisms when the cause is present and outcome is absent, deviant case analysis can aid theory development by pointing to other variables that can explain why a mechanism breaks down.[5] Specifically, the U.S.-Japan case is an important deviant case with respect to the LS mechanism, in which all the components of the mechanism are present, yet the outcome does not materialize. Based on Japan's success in key leading sectors, such as semiconductors and electronics, many scholars predicted that Japan would overtake the U.S. during this period, yet an economic power transition never occurred.[6] In addition, the case also serves as a check on the GPT mechanism. If the empirical information shows that all the components of the GPT mechanism were also present in this case, it should weaken the credibility of the GPT mechanism.[7]

One natural source of concern with my case selection strategy is selection on both the explanatory and dependent variable, which has been described as the "most egregious error" of case selection.[8] In variance-based interpretations of causality, the mean effect of causes is derived from evidence of covariation between values of the explanatory and dependent variable across a range of cases. Since representativeness is the key criterion for case selection, selecting cases that vary on both the independent and dependent variable is encouraged.[9] Some scholars advocate for random selection.[10]

I am not studying the average treatment effect of one unit of technological change on the likelihood of an economic power transition. My interest is in the causal mechanisms that link major technological revolutions with the rise and fall of great powers. Since this is a rare outcome, there are not many (1,1) cases. Random selection would lead to studying many cases without a technological revolution and hegemonic transition. Rooted in a mechanism-based approach to

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[3] Modelski and Thompson 1996, 69.
[4] Clark 2014, 220.
[5] Beach and Pedersen 2018, 861-863. Goertz (2017, 66) labels cases where the causal mechanism is present, but the outcome is absent (X = 1, Y= 0) as "disconfirming" or "falsifying" cases.
[6] Gilpin (1996, 428) summarizes, "The appreciation of Japan's increasing strength in one high-tech industry after another has led many American and European observers to fear that Japan will acquire a monopoly of the commanding technologies of the third industrial revolution."
[7] With respect to the GPT mechanism, this case is less relevant, since the empirical analysis reveals that the causal mechanism and outcome are not present (X = 0, Y = 0). One could think that this case shows that if the GPT mechanism is not present, then a shift in productivity leadership is less likely. However, while we have a relatively clear notion of what causes economic power transitions, there are countless explanations for non-shifts in economic leadership, which makes these types of cases conceptually problematic. Mahoney and Goertz 2004.
[8] King et al. 1994, 142; see also Achen and Snidal 1989.
[9] For a critique of representativeness as a criterion for case selection, see Goertz 2017, 247-252.
[10] Fearon and Laitin 2008; Herron and Quinn 2016.

causality, I choose instead to prioritize typical cases where the cause and outcome are present.[11] This approach is consistent with recent discussions of case selection for studying causal mechanisms in small-N research, which have moved toward favoring the selection of cases that are positive on the main independent variable of interest and the dependent variable.[12]

Justification for GPT and LS Selection in IR-2 Case

This section clarifies my selection criteria for the technologies I trace in the IR-2 case. I focus on the automobile, chemical, electrical equipment, and steel industries as candidate leading sectors. These choices are informed by scholars who study the implications of technological change during this period from a LS perspective. The first three sectors feature in the standard rendering of the IR-2 by prominent historical accounts, which centers major discoveries in chemistry and electricity, as well as the invention of the internal combustion engine.[13] Among those who study the effect of technological revolutions on the balance of power, there is near-consensus on the chemical and electrical industries as technologically progressive, fast-growing industries during this period.[14] The automobile industry, spurred by the invention of the internal combustion engine, also appears in some classification schemes for leading sectors in the IR-2,[15] though others reason that automobiles only emerged as a leading sector in later periods.[16]

The automobile, chemical, and electrical industries all experienced prodigious growth during the IR-2, meeting the primary qualification for leading sectors. According to statistics from the U.S. Census, the percent increase in value added by manufacture in each of these industries was much higher than the average across all industries from 1899 through 1909. In fact, in terms of percent growth in value added by manufacture in this period, automobiles and electricity boasted the two highest growth rates among industries with products valued at more than $100 million.[17]

I also consider developments in steel as a possible source of leading sector product cycles. It is hard to ignore the explosive growth of the steel industry in both Germany, where it multiplied over 100-fold from 1870 to 1913, and the U.S., where it multiplied around 450 times over the same period.[18] In addition, many scholars list steel as one of the leading sectors that affected the economic power balance in the IR-2.[19] Rostow identifies steel as part of "the classic sequence" of "great leading sectors."[20]

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[11] Beach and Pedersen 2019, 97-98; Mahoney 2010.
[12] Goertz and Mahoney 2012, 177-191; Schneider and Rohlfing 2013.
[13] Hull 1996, 192, 196; Landes 1969, 4; Schumpeter 1939, 167.
[14] Gilpin 1987, 309; Kim and Hart 2001, 304; Modelski and Thompson 1996, 87-88; Ostry and Nelson 1995, 43.
[15] Gilpin 1987, 309; Kim and Hart 2001, 304.
[16] Gilpin 1975; Kurth 1979, 26; Moe 2009, 218-219; Thompson 1990, 213.
[17] For statistics on automobiles and electricity (captured in the "electrical machinery, apparatus, and supplies" category), see Department of Commerce 1913, 40; for statistics on the chemical industry ("chemicals and allied products"), see Department of Commerce 1913, 53).
[18] Calculations based on crude steel output figures in Mitchell 1998, 466-467; Mitchell 1993, 356-358.
[19] Kurth 1979; Modelski and Thompson 1996, 69; Gilpin, 1975, 67; Rostow 1978, 105.
[20] Rostow 1978, 105.

I analyze chemicalization, electrification, the internal combustion engine, and interchangeable manufacture as the potential drivers of GPT-style transformations in the IR-2. Of these four, electricity is the prototypical GPT. It is "unanimously seen in the literature as a historical example of a GPT."[21] Electricity is one of three technologies, alongside the steam engine and ICT technology, that feature in nearly every article that seeks to identify GPTs throughout history.[22] Electrical technologies possessed an enormous scope for improvement, fed into a variety of products and processes, and synergized with many other streams of technological development. Empirical efforts to identify GPTs with patent data provide further evidence of electricity as a GPT in this period.[23]

Like advances in electricity, clusters of innovations in chemicals and the internal combustion engine not only spurred the rapid growth of new industries but also served as a potential source of GPT trajectories. Historians of technology pick out chemicalization, alongside electrification, as one of two central processes that transformed production routines in the early 20th century.[24] Historical patent data confirms that chemical inventions had the potential to influence a wide variety of products and processes.[25]

In line with GPT classification schemes by other scholars, I also evaluate the internal combustion engine as a candidate GPT, given its potential to replace the steam engine of a prime mover of many industrial processes.[26] After its introduction, many believed that the internal combustion engine would transform a range of manufacturing processes with smaller, divisible power units.[27]

Lastly, I examine innovations in machine tools as a candidate GPT in this period. Though the machine tool industry was neither a new nor especially fast-growing sector, it did play a central role in further advancing the mechanization of machine-making first incubated in the IR-1. The advance of interchangeable manufacture, or the American system, owed much to advances in turret lathes, milling machines, and other machine tools that improved the precision of cutting and shaping metals. Rosenberg's seminal study of "technological convergence" between the American machine tool industry and metal-using sectors highlighted how innovations in metalworking machines transformed production processes across a wide range of industries.[28] Following Rosenberg's

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21 Ristuccia and Solomou 2014.
22 Field 2008, 10.
23 Petralia 2020a; Petralia 2020b.
24 Nelson and Winter 1982, 261; Noble 1975, 18; Landau and Rosenberg 1992, 76. Rosenberg 1998 highlights "chemical engineering" as the GPT of note this period. Departing slightly from Rosenberg's account, I take the principles of chemical transformations as the GPT, which spread across many industries. The profession of chemical engineering, in my analysis, is an institutional adaptation to systematize skills related to chemical production systems.
25 Moser and Nichols 2004. Notably, Moser and Nichols (2004, 393) find that developments in chemicals "fulfill the criteria for GPTs at least as well as those in electricity." For further discussion of whether electrical technologies better fit the characteristics of a GPT than chemical technologies, see Petralia 2020a.
26 Lipsey et al. 2005, 133; Jovanovic and Rousseau 2005.
27 Du Boff 1967, 514. In 1894, an American technical journal speculated that the replacement for the steam engine would be the internal combustion engine, which they claimed "may be regarded as the motor of the future." *Power and Transmission*, IX (1894), 15
28 Rosenberg 1963, 423.

interpretation, historians recognize the nexus of machine tools and mechanization as one of the key technological trajectories during this period.[29]

While there is substantial overlap between the candidate GPTs and leading sectors in the IR-2, as reflected in Supplementary Table 2, two key distinctions are worth emphasizing. First, the GPT categorization includes the effects of machine tools on interchangeable manufacture. Existing scholarship on leading sectors overlooks the impact of machine tools in this period, possibly because the industry's total output did not rank among the largest industries and innovation in machine tools was relatively incremental.[30] One survey of technical development in machine in tools from 1850 to 1914 described the landscape as "essentially a series of minor adaptations and improvements."[31] Relatedly, steel, commonly regarded as a LS, is not considered a candidate GPT. Under the GPT mechanism, innovations in steel are linked to a broader GPT trajectory of interchangeable manufacture.

Supplementary Table 2: Key Sources of Technological Trajectories in the IR-2

<u>Candidate Leading Sectors</u>	<u>Candidate GPTs</u>
Steel industry	Interchangeable manufacture
Electrical equipment industry	Electrification
Chemical industry	Chemicalization
Automobile industry	Internal combustion engine

Second, even though some technological changes, such as electricity, are considered both candidate leading sectors and GPTs, there are different interpretations of *how* developments in these technological domains translated into an economic power transition. In his analysis of leading sector growth rates, Thompson expresses a similar logic, "Although knowing this does not tell us exactly why the British lead faltered and was overtaken, it does help narrow where to look."[32] The process-tracing evidence will support either the GPT or LS interpretation. Two trajectories diverge in a yellow wood, and the case study evidence shows which one electricity traveled.

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[29] Thomson 2010, 4; Mosk 2010, 22; Nelson and Winter (1982, 261) identify a "natural trajectory," similar to a GPT trajectory, in mechanization. Note: one account Lipsey et al. (1998, 46-47) categorizes the 19th-century machine tool industry as a "near GPT" because the range of use of machine tools was restricted to manufacturing.
[30] According to one estimate of the U.S. machine tool industry's size in 1914, its total output only amounted to $31.5 million. Bureau of the Census 1918, 269.
[31] Floud 1976, 31.
[32] Thompson 1990, 226.

Extended Discussion of IR-1 Case

This section elaborates on the IR-1 case by highlighting two competing interpretations of how the IR-1 influenced an economic power transition: GPT diffusion based on advances in iron vs. LS product cycles based on cotton textile innovations. Support for the former points to Britain's institutional advantages in widening the base of mechanically-skilled engineers as critical to its successful adaptation to the IR-1.

Impact Timeframe: Time-series data on output growth of 26 industries, which accounted for around 60 percent of Britain's industrial production, helps differentiate the growth schedules of the cotton textiles and iron industries. According to this data, the major upswing in British industrialization took place after 1815, when the aggregate growth trend increased from 2 percent to a peak of 3.8 percent by 1825. In line with the LS model's expectations, Britain's cotton textile industry grew exceptionally fast following major technological innovations in the 1760s but experienced a deceleration in output growth from the 1780s onward. Based on the relatively early peak of the cotton industry's expansion, two scholars conclude that "it appears unlikely that cotton played the major role in the post-1815 upswing in British industrialization."[33]

Following a GPT trajectory, growth in iron goods was more in line with when British industrialization outpaced its rivals. Starting in the 1780s, the growth rate of the British iron industry accelerated to a peak of about 5.3 percent in the 1840s.[34] "Compared to cotton textiles, change in iron was gradual, incremental, and spread out over a longer period of time," Moe writes.[35] This timeline tracked with that of Britain's mechanization, linked to the expanded uses of iron in machine-making. According to British patent data from 1780 to 1849, the share of mechanical engineering patents among the total number of patents increased from an average of 18 percent in the decade starting in 1780 to a peak of 34 percent in the one starting in 1830.[36]

Phase of Relative Advantage: Developments in cotton and iron also diverged greatly with respect to this dimension. The former is most likely to support the LS mechanism's emphasis on monopoly profits. Britain's cotton textile industry increased output by 2,200 percent from 1770 to 1815, and cotton's share of Britain's major exports increased from 1 percent to 39.6 percent.[37]

On the other hand, historians generally accept that the cotton industry was much more significant for enhancing Britain's trade balance than for boosting economic productivity.[38] According to one

[33] Greasley and Oxley 2000, 114. There is general acceptance that the cotton industry's influence on British economic growth peaked relatively early. Farnie 2003, 734.
[34] Greasley and Oxley 2000. Trend growth for cotton stayed above that of the aggregate industrial economy in the period to 1860, so if following a strict definition of a leading sector, then cotton should be classified as a leading sector from the period of 1760 to 1860.
[35] Moe 2007, 81.
[36] MacLeod and Nuvolari 2009, 224.
[37] Harley 1982, 268-269; Moe 2007, 38-39.
[38] Farnie 2003, 734; Tomory 2016, 157.

estimate of the cotton industry's contribution to Britain's economy between 1800 and 1860, the industry accounted for 43 percent of the three-fold increase in the value of exports but only eight percent of the three-fold increase in national income.[39] Revised estimates, which incorporate a weighting scheme that indexes industry data to price and quantity trends from the 1841 Census, have also muted the role of the cotton industry in the earlier years of Britain's industrialization. Cotton represented only 1 percent of industrial production in 1770 and only 8 percent in 1815.[40]

Britain's iron industry was not as ripe for LS product cycles, as it accounted for a much smaller proportion of Britain's exports and national income than cotton.[41] Instead, its impact materialized through the diffusion of iron machinery across a wide range of sectors. In this area, Britain was more successful than its industrial rivals. Writing in 1786 in their *Voyages aux Montagnes,* French observers F. and A. de la Rochefoucauld-Liancourt commented on Britain's relative advantage in the widespread adaptation of the use of iron:

> The great advantage [their skill in working iron] gives them as regards the motion, lastingness and accuracy of machinery. All driving wheels and in fact almost all things are made of cast iron, of such a fine and hard quality that when rubbed up it polishes just like steel. There is no doubt but that the working of iron is one of the most essential of trades and the one in which we are most deficient.[42]

To be clear, France's iron deficiency was not due to its inability to produce key innovations. In fact, France was the world's center of science from the late eighteenth century until the 1830s.[43] Rather, as the below quote illustrates, Britain's industrial rivals fell behind in "diffused average technology" and the "effective spread of technical change more widely." Mathias writes:

> It is remarkable how quickly formal knowledge of 'dramatic' instances of new technology, in particular steam engines, was diffused, and how quickly individual examples of "best-practice" technology in "show piece" innovations were exported. The blockage lay in the effective spread of technical change more widely — diffused average technology rather than single instances of best- practice technology in "dramatic" well-publicized machines.[44]

Breadth of Growth: Trade data, patent data, and estimates of sectoral contributions to economic growth all support an assessment of broad-based productivity growth in Britain.[45] These confirm

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[39] Farnie 2003, 735. The British cotton textile industry accounted for more than half of British exports by 1831 but never more than 7-8 percent of national income. Moe 2007, 37.
[40] Harley 1982, 269.
[41] Moe 2007, 86.
[42] Armytage 1961, 93.
[43] Moe 2007, 42.
[44] Mathias 1975, 102.
[45] Macleod 1988, 148; McCloskey 1981, 114; Temin 1997, 76.

"the empirical fact that this was an economy with extensive technological change, change that was not confined to leading sectors or highly visible areas of activity."[46]

Input-output analysis, which sheds light on the linkages between industries, suggests that improvements in the working of iron were central to spurring widespread productivity growth. To better understand the interrelationships among industries during the industrial revolution, Horrell et al. constructed an input-output table for the British economy in 1841. Across the 17 industries included in the input-output analysis, the two industries most closely associated with mechanization — the metal manufacture and metal goods industries — scored the highest on combined backward and forward linkages.[47] These were "the lynchpins of linkage effects" during this period.[48]

Patent indicators confirm these results. Consider two ways of evaluating a dataset on patents issued in Britain between 1711-1850. Assigning patents to standard industry taxonomies reveals that the textile industry contributed to 15 percent of the patents issued over the period, making it the most inventive industry in aggregate terms. However, if patents are allocated to groups defined by general techniques as opposed to industry sectors, the same dataset underscores the underlying drive force of mechanical technology: It is linked to almost 50 percent of all British patents during this period.[49]

Institutional Complementarities — GPT skill infrastructure in the IR-1: Britain benefited from a repository of engineers skilled in the precision metalworking of large-scale iron machinery.[50] Responsible for not just the first installation of a machine but also further refinement and maintenance, machine makers and mechanical engineers reduced the adoption costs for mechanization.[51] While Britain's industrial rivals could adopt the most high-profile, showpiece machines with relative ease, they struggled to adopt "diffused average technology."[52] "It was exactly in the skills associated with the strategic new industries of iron and engineering that [Britain's] lead over other countries was most marked," argues Mathias.[53] France suffered from a "human capital lag" in "engineers with skills in machinery," which hampered its adoption of mechanization.[54]

Why did this repository of engineering skills develop more fruitfully in Britain than in its industrial rivals? British institutions adapted to widen the skill base for mechanization. First, institutes dedicated to training mechanical engineers helped diffuse ironmaking and machine-making skills. A flurry of trade associations that catered to a new class of mechanical and civil engineers sprung up in

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46 Bruland 2004.
47 Horrell et al. 1994, 555.
48 Horrell et al. 1994, 557.
49 Sullivan 1990, 354. Another analysis of British patents from 1780-1849 finds that the share of mechanical engineering patents grew from 17 percent at the start of the period to about 30 percent by the end. MacLeod and Nuvolari 2009, 223.
50 Berg 1985, 42; Mathias 1975, 107-108.
51 MacLeod and Nuvolari 2009, 227.
52 Mathias 1975, 102.
53 Mathias 1969, 129.
54 Moe 2007, 94.

the 1820s.[55] Critical centers established in the first half of the 19th century included the Andersonian Institution in Glasgow, the Manchester College of Arts and Sciences, the School of Arts in Edinburgh, the Mechanical Institution in London, the Society for the Diffusion of Useful Knowledge, and hundreds of Mechanics' institutes.[56] These institutes helped to absorb knowledge from foreign publications on science and engineering, recruit and upskill new mechanical engineers from a variety of trades, and spread mechanical engineering knowledge more widely.[57]

Britain's institutional advantage was rooted in the system of knowledge diffusion that connected engineers with entrepreneurs, cities with the countryside, and one social class with another. The institutes that trained mechanical engineers were part of a broader "mushrooming of associations" that spread technical knowledge in early 19th century Britain.[58] By the mid-nineteenth century there were 1,020 such associations in Britain with a total membership of approximately 200,000, making these networks essential to any explanation that links human capital to Britain's industrial ascent.[59] As a result, the British system of the early nineteenth-century had no match in its abundance of people with "technical literacy."[60]

The French system, by comparison, lacked similar linkages and collaborations between highly educated engineers and local entrepreneurs.[61] Though France produced elite engineers at schools like the Ecole polytechnique, it trained too few practitioners to widen the base of mechanical engineering talent.[62] For instance, Napoleon's early 19th-century reform of France's higher education system emphasized the training of experts for narrow political and military ends, which limited the ability of trainees to build connections with industry.[63] Through the mid-1830s, only one third of École Polytechnique graduates entered the private sector.[64] "[T]he (British) system of knowledge diffusion was vastly superior to the French," summarizes Moe.[65]

Extended Discussion of IR-3 Case

This section expands on the IR-3 case. To account for sustained U.S. economic leadership in the IR-3, this section traces the developments of the IR-3 in the U.S. and Japan across the three dimensions

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55 Jefferys 1946, 17.
56 Marsden 2004, 405; Pollard 1965, 180-181. By 1850 there were around 700 Mechanics' institutes across Great Britain. Birse 1983, 62.
57 Musson and Robinson 1960; Musson 1969.
58 Crafts 1996, 199.
59 Mokyr 2002, 66.
60 Mokyr 2002, 73.
61 Jacob 1997, 184; Crouzet 1967, 239.
62 This is the commonly held view. See, for example, Kindleberger 1976, 13. Some French middle-level technical schools like the Ecoles d'arts et metiers did implement reforms that widened access to mechanical engineering instruction. Day 1978, 444.
63 Crouzet 1967, 239; Lundgreen 1990, 39; Moe 2007, 43.
64 Ahlström 1982, 44.
65 Moe 2007, 49.

that differentiate GPT from LS trajectories. It then supports my contention that the U.S. was particularly effective at adjusting to computerization because of its GPT skill infrastructure.

Impact Timeframe: The advance of computerization, like past GPT trajectories, demanded a prolonged period of organizational adaptation and complementary innovations. In the 1960s, mainframe computers powered by integrated circuits marked the early use of computers for a limited range of commercial purposes, such as producing bank statements and managing airline reservations. Spurred by the introduction of the personal computer in the 1970s, the functionalities of computers greatly expanded.[66] With the internet's rise in the 1990s, new information and communication networks further spread computerization to different business models, such as e-commerce.[67] Alongside this stream of complementary technical advances, firms needed time to build up their computer capital stock and re-organize their business processes to match the needs of information technology.[68]

The gradual diffusion of computers led many observers to bemoan the computer revolution's failure to induce a surge of productivity growth. In 1987 the renowned economist Robert Solow distilled this "productivity paradox" in a famous quip: "We see the computers everywhere but in the productivity statistics."[69] A decade later, however, the growing adoption of information technology triggered a remarkable surge in U.S. productivity growth.[70] It took some time, but the American economy did eventually see the computers in the productivity statistics.

The landscape of U.S.-Japan technology competition looks very different when accounting for this elongated impact timeframe from the emergence of computerization to its widespread diffusion. Japan's control over key segments of ICT production in the 1970s and 1980s did not correspond to an advantage in GPT diffusion. A more patient outlook illuminates that the delayed impact of computerization aligns with when the U.S. extended its productivity lead over Japan. After 1995, while Japan's economic rise stalled, labor and total factor productivity grew rapidly for a decade in the U.S. The difference was that the U.S. benefited greatly from an ICT-driven productivity acceleration.[71]

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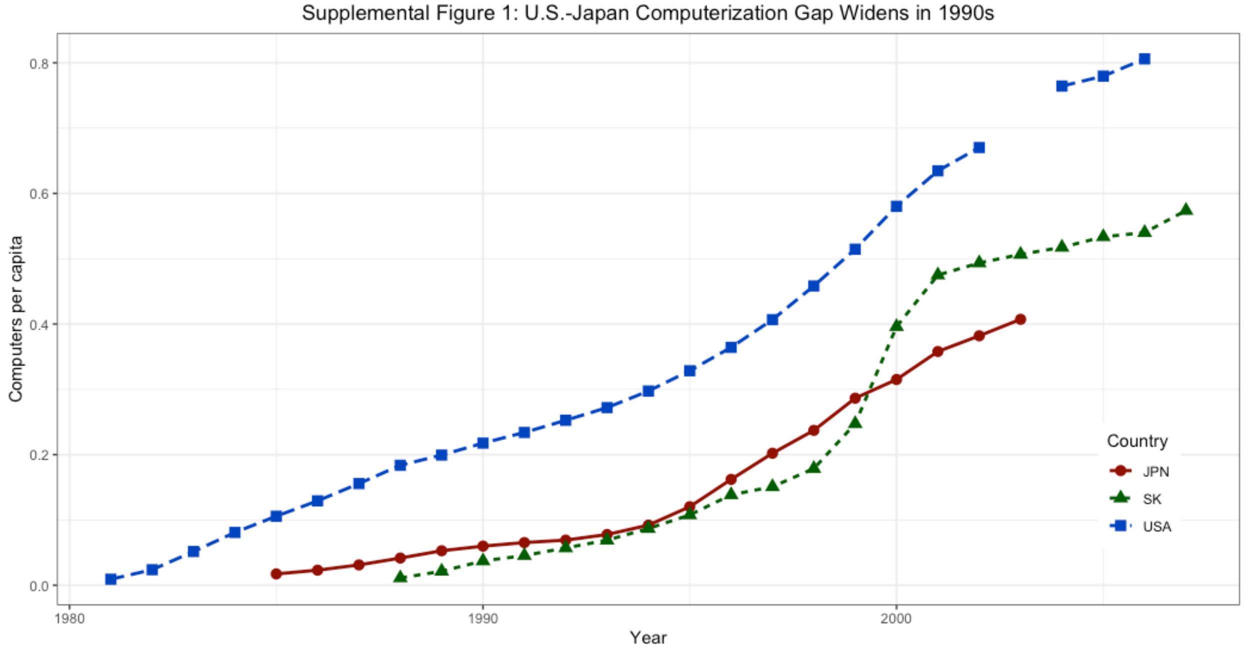
66 Bruland and Mowery 2006, 369. Langlois (2013, 155) recaps, "By the early 1980s, a microcomputer (personal computer) costing $3,500 could do the work of a $10,000 stand-alone word processor, while at the same time keeping track of the books like a $100,000 minicomputer and amusing the kids with space aliens like a 25-cents-a-game arcade machine."
67 Gordon 2016, 441-442.
68 Brynjolffson et al. 2017, 23-25.
69 David 1990, 355.
70 Crafts 2002; Gordon 2016, 576; Oliner and Sichel 2000.
71 Fueki and Kawamoto 2009, 325; Crafts 2002.

Phase of Relative Advantage: Though Japan excelled in the production of computers and electronics, it fell behind in the general pace of computerization across the economy. As Supplemental Figure 1 reveals, the gap between the U.S.-Japan in computerization widened in the 1990s. In fact, South Korea, which lagged behind Japan in generating new innovations in computer systems, surpassed Japan in computer usage rate during the 1990s. Taken together, these indicators suggest that Japan's problem was with GPT diffusion, not innovation.

Supplemental Figure 1: U.S.-Japan Computerization Gap Widens in 1990s



Source: Milner and Solstad 2021; Comin 2011, 381.

To be sure, Japan eventually adopted the GPT trajectory associated with ICTs. Like all advanced economies at the frontier, Japan could draw from the same technology pool as America. Using a growth accounting framework that accounts for cyclical factors, Fukei and Kawamoto trace Japan's post-2000 resurgence in TFP growth to the extension of ICT revolution to a broader range of IT-using sectors.[72] By then, however, Japan was at least five years behind the U.S. in taking advantage of computerization.

Breadth of Growth: Lastly, Japan's advantages were concentrated in a narrow range of ICT-producing industries, whereas the U.S. benefited from broad-based productivity growth. Alongside the dispersion of ICTs throughout the U.S. economy, the sources of productivity growth also spread out. In the U.S., spillovers from ICT advances, especially in services, contributed to economy-wide TFP growth. Industry-level patterns of TFP growth reveal that U.S. productivity growth became noticeably more broad-based after 1995, a trend that accelerated further after 2000.[73]

In contrast, Japan's advantages in the IR-3 were limited to a narrow range of sectors. After 1995, Japanese productivity growth remained localized, only transitioning to a more broad-based pattern

[72] Fueki and Kawamoto 2009.
[73] Basu and Fernald 2007; Inklaar and Timmer 2007.

after 2000.[74] Porter's exhaustive account of national competitiveness across leading economies describes Japan as a "study in contrasts," with some of the most internationally competitive industries found side by side with some of the most uncompetitive.[75] Caught up in the hype over Japan's success in some leading sectors, analysts "often unwittingly generalize[d] from the experience of particular successful industrial sectors and tend[ed] to ignore the sectors in which Japanese industry ha[d] been less successful."[76]

Institutional Complementarities — GPT skill infrastructure in the IR-3: The U.S. systematized the engineering skills required for computerization in computer science, the latest in a line of engineering disciplines that emerge in the wake of a GPT. By 2007, some 20 percent of software engineers in the U.S. possessed a graduate school degree, compared to just 10 percent in Japan.[77] The U.S. system of higher education was more well-suited to cultivating the necessary skill infrastructure for widespread computerization.[78]

U.S. universities successfully adapted to changes in the computerization trajectory. Led by pioneers like Stanford and the Association of Computing Machinery, U.S. institutions piloted new training programs in computer science. These adaptations paved a sustainable pathway for the transfer of technical know-how gained by experienced computer specialists and programmers to up-and-coming computer engineers.[79] From 1979 to 1989, the number of undergraduate computer science degrees awarded annually in the U.S. grew by more than a factor of three. The number of individuals who held doctorates and taught computer science also more than tripled over the same period.[80] In 2011 computer science became the most popular choice of major for Stanford undergraduates.[81] The recognition of computer science as an independent discipline, as evidenced by the early and rapid growth of computer science departments in the U.S, helped to systematize the skills necessary for the spread of computerization.[82]

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[74] Wirkierman 2014.
[75] Porter 1990, 394.
[76] Kitschelt 1991, 454.
[77] Nakata and Miyazaki, 2011, 100; cited in Cole 2013, 3.
[78] The U.S. also benefited from a system open to tapping foreign software talent. Compared to Japan, the U.S. was better able to draw upon a foreign supply of ICT talent through high-skilled immigration and software offshoring. Crucially, imported talent widened the base of software engineering talent in America. Arora et al. (2013, 772) write, "Relatively few of these imported experts may have been software architects of the highest order, capable of undertaking transformative innovation. However, creating, testing, and implementing software for IT innovation requires both fundamental innovators and programmers undertaking more routine and standardized kinds of software engineering. America's ability to tap into an increasingly abundant (and increasingly foreign) supply of the latter may have raised the productivity of the former and enabled American firms to outpace their rivals."
[79] Vona and Consoli 2014, 1404.
[80] National Research Council 1992, 47.
[81] Meyer 2012.
[82] Steinmueller 1996, 42. It is important to note that the U.S. military played a key role in cultivating the computer science discipline in its early years. Beginning in the 1960s DARPA helped create centers of excellence in computer science, which disseminated computer science skills to other research universities and commercial markets. National Research Council 1999, 221; Newell 1984.

Japanese universities, on the other hand, were slow to adapt their curriculum to the new field of computer science. In both 1997 and 2007, the Information Processing Society of Japan modeled its computing curriculum revisions on American efforts that had happened six years earlier. The University of Tokyo, Japan's leading university, did not establish a separate department of computer science until 1991, which was 26 years later than Stanford.[83] Overly centralized governance of universities inhibited the development of computer science as an independent discipline in Japan.[84] "The organizational and disciplinary flexibility of U.S. universities in computer science has not been matched in any of the competing economies," Hart and Kim conclude.[85]

In both the IR-1 and IR-2 cases, the eventual technological leader cultivated a GPT skill infrastructure that allowed for dense connections between educational institutions and industry. This was also true for the U.S. in the IR-3 case. The U.S.'s sustained economic leadership benefited from extremely close partnerships between universities and industry in computer science.[86] This was rooted in the autonomy of state governments to support linkages between public universities and industry demands for research.[87] Closer university-industry linkages in the U.S. system of higher education, compared to arrangements in Japan or Europe, provided a much "thicker basis" for skill adjustments to the trajectory of computerization.[88]

Japan maintained a very different skill infrastructure for computerization. Centralized control of universities, exercised through the Japanese Ministry of Education, Sport and Culture, hampered cooperative networks between universities and industry.[89] Bureaucratic rivalries prevented universities from finding alternative sources of funding, which limited reforms such as partnerships between new departments of information science and corporate labs where much of the computing talent was concentrated. Japan's overall budget level for university facilities in 1992 remained the same as it was in 1975. Additional government funds went, instead, to independent centers of excellence, which impoverished the training of Japan's basic researchers and technicians.[90]

Application of GPT Diffusion to U.S.-China Technological Competition

In one of the implications of GPT diffusion for how AI breakthroughs could bring about a possible U.S.-China power transition, I argue that the U.S. is better positioned than China to implement AI at scale. This section provides more context and evidence for this claim.

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83 Cole 2013, 8.
84 Cole 2013, 9-10; Kitschelt 1991, 482.
85 Hart and Kim 2002, 10.
86 Moe 2007, 221.
87 Drezner 2001, 22-23.
88 Hart and Kim 2002, 10.
89 Drezner 2001, 20-22.
90 Anderson and Myers 1992, 565, 569.

In debates over China's scientific and technological power, complex dynamics get reduced to a magic word — innovation.[91] Whether China can generate novel technologies is often the crux of debates over China's growing scientific and technological capabilities and a potential U.S.-China power transition. For Rapkin and Thompson the prospect of China overtaking the U.S. as the leading power is dependent on "China's capacity to innovate" — specifically as it relates to revolutionary technological changes that allow challengers to leapfrog the leader in economic and military competition.[92] "If...China's innovativeness continues to lag a considerable distance behind that of the U.S., then China overtaking the U.S. might wait until the twenty-second century," they posit.[93] China's innovation imperative, as Kennedy and Lim describe in language familiar to LS analysis, is motivated by the "*monopoly rents* generated by new discoveries."[94]

Innovation-centric views of China's AI capabilities paint an overly optimistic picture of China's challenge to U.S. technological leadership. Those bullish on China's long-term rise point to China's impressive performance along traditional indicators of innovation, such as R&D expenditures, scientific publications, and patents, which map China's capacity to generate new breakthroughs.[95] Arguments that China is poised to overtake the U.S. as an AI superpower also tend to rely on these indicators.[96]

If forecasts of U.S.-China competition in AI were centered on GPT diffusion theory, they would focus more on China's capacity to widely adopt AI advances. In this scenario, it is neither surprising nor particularly alarming that China, like other great power contenders such as Japan in the IR-3, Germany in the IR-2, France in the IR-1, is contributing to fundamental innovations in AI. One country cannot corner all the innovations in a GPT like AI. The key point of differentiation will be the ability to adapt and spread AI innovations across a wide array of sectors.[97]

This diffusion-centric perspective suggests that China is far from being an AI superpower. Trends in the intensive adoption of information and communication technologies (ICTs) reveal that there is a large gap between the U.S. and China. China ranks number 83 in the world on the International Telecommunication Union's ICT development index, which is a composite of ICT readiness (the level of networked infrastructure and access to ICTs), ICT intensity (the level of use of ICTs in the society) and ICT impact (the results/outcomes of more efficient and effective ICT use).[98] While China has achieved some impressive successes in ICT diffusion across consumer-facing applications

[91] Historians have decried the disproportionate attention paid to innovation — a phenomenon Edgerton labels "innovation-centrism." Edgerton 2010; Godin 2015.
[92] Rapkin and Thompson 2003, 333. Tellis (2013, 112) states that the U.S. must "sustain its dominance in the new leading sectors of the global economy" to check China's growing power.
[93] Rapkin and Thompson 2003, 333.
[94] Kennedy and Lim 2018, 555. Emphasis mine.
[95] Kennedy 2015, 284.
[96] See, for example, Allison and Schmidt 2020; Frey and Osborne 2020. For a critique of some of these indicators, see Ding 2019.
[97] Naughton has argued that China needs "unprecedented productivity growth from the service sector" to sustain its growth. Naughton 2018, 168.
[98] International Telecommunication Union 2017.

— such as the spread of mobile payments and e-commerce — Chinese businesses have been slow to embrace digital transformation.[99] In fact, it is often Chinese scholars and think tanks that acknowledge these deficiencies. According to an Alibaba Research Institute report, China significantly trails the U.S. in penetration rates of many digital technologies across industrial applications, including digital factories, industrial robots, smart sensors, key industrial software, and cloud computing.[100] In 2017, U.S. firms devoted 29 percent of their total IT budget on cloud expenditures, more than double the comparable rate for Chinese firms.[101]

China's limitations in diffusing advances in robotics, a key application sector of AI, provide further confirmatory evidence. On the one hand, China leads the world in total installations of industrial robots. China added 154,000 industrial robots in 2018, which was more than the U.S. and Japan combined.[102] On the other hand, China's robot rollout is much less impressive when assessing the proportion of its manufacturing base that has adopted robotic technology.[103] In 2018, Japan and the U.S. ranked 4th and 8th, respectively, in robot density, as measured by the number of robots installed per 10,000 manufacturing workers. China placed a distant 20th in robot density.[104]

At present, the U.S. is better positioned than China to develop the skill infrastructure for the AI revolution. It is not just that the U.S. has cultivated the widest pool of AI talent.[105] The connective tissue that enmeshes AI engineers in cross-cutting networks with entrepreneurs and scientists, as previous industrial revolutions have demonstrated, is essential to successful GPT diffusion. While the AI trajectory is still evolving, some preliminary indicators suggest that this connective tissue is especially strong in the U.S. It leads the world with the highest number of academic-corporate hybrid AI publications, co-authored by at least one researcher from industry and academia, more than doubling the amount from China.[106]

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[99] Kannan and Thomas 2018. Recently, some analysts have argued that China's rising S&T prowess comes from its strategic advantage in deploying innovations at scale, which benefits from a globalized, open R&D system. See, for example, Breznitz and Murphree 2011; de La Bruyère and Picarsic 2020. These analyses draw from a few examples of Chinese success at large-scale deployment in domains such as high-speed rail and mobile payments. This section's comprehensive evaluation cautions against overestimating China's diffusion capacity.

[100] Alibaba Research Institute 2019. For other Chinese-language reports that cover China's struggles to transfer leading technologies from frontier firms to small and medium enterprises, see Synced 2020; Techxcope 2020.

[101] Kannan and Thomas 2018.

[102] Based on statistics from International Federation of Robotics (IFR) 2019.

[103] The proportional figure is "the most commonly used metric" in comparing nations in terms of robot adoption. Atkinson 2019.

[104] Based on statistics presented in IFR 2019. Similar indicators show that the diffusion rate of welding robots in China is at least two times lower than in Germany and Japan. Pang 2019. Though some project that China will eventually lead the world in robot density (Atkinson 2019), China's installations of industrial robots have declined in recent years.

[105] According to data from the end of 2017, China ranks second to the U.S. in terms of total AI scientists and engineers. Interestingly, China is more competitive with respect to AI implementers. Based on where the most productive and highly cited AI scientists are located, China ranks sixth in the world, with the U.S. also ranking first in this metric. SCMP Research 2020.

[106] Zhang et al. 2021, 23. This finding is based on a dataset of peer-reviewed AI publications between 2015 and 2019. For more on the challenges of science-industry linkages in China, see Tagscherer 2015.

Moreover, the U.S. approach to AI standardization could be more optimal for coordinating information flows between labs working on fundamental AI advances and specific application sectors. The U.S.'s market-mediated, decentralized standardization system may be particularly favorable for advancing the development of AI, a domain characterized by significant uncertainty about future trajectories.[107] In such fields, governments confront a "blind giant's quandary" when attempting to influence technological development through standards-setting.[108] The period when government involvement can exert the most influence over the trajectory of an emerging technology coincides with when the government possesses the least technical knowledge about the technology. Government intervention, therefore, could lock in inferior AI standards compared with market-driven standardization efforts.

In that light, China's state-led approach to technical standards development could hinder the sustainable penetration of AI throughout its economy. For example, the Chinese central government plays a dominant role in China's AI Industry Alliance, which has pushed to wrest leadership of standards setting in some AI applications away from industry-led standardization efforts.[109] Excessive government intervention has been a longstanding weaknesses of China's standardization system, producing standards not attuned to market demands and bureaucratic rivalries that undermine the convergence of standards.[110] Wang Ping, known as "China's leading standards guru,"[111] has argued that China needs to reform its standardization system to allow private standards development organizations more space to operate, like the U.S.'s Institute of Electrical and Electronics Engineers in the U.S. and the European Committee for Electrotechnical Standardization.[112]

Additional References Cited in Supplementary Appendix

Achen, Christopher H., and Duncan Snidal. "Rational Deterrence Theory and Comparative Case Studies." *World Politics* 41, no. 2 (January 1989): 143–69. https://doi.org/10.2307/2010405.

Alibaba Research Institute. "From Connected to Empowered: Smart+ Assisting the High-Quality Development of China's Economy [从连接到赋能：'智能+'助力中国经济高质量发展]," March 11, 2019. http://www.cbdio.com/BigData/2019-03/18/content_6049452.htm.

Allison, Graham, and Eric Schmidt. "Is China Beating the U.S. to AI Supremacy?" Belfer Center for Science and International Affairs, August 2020.

Anderson, Alun, and Fred Myers. "Japanese Academics Bemoan the Cost of Years of Neglect." *Science* 258, no. 5082 (October 23, 1992): 564–70.

Armytage, W. H. G. *A Social History of Engineering*. London: Faber & Faber, 1961.

107 Chan et al. 2019.
108 David 1987; David 1995.
109 Luong and Arnold 2021, 8.
110 Ernst 2011, 85; Breznitz and Murphree 2013.
111 Yates and Murphy 2019, 336.
112 Wang and Zheng 2018.

Atkinson, Robert D. "Robotics and the Future of Production and Work." Information Technology and Innovation Foundation, October 15, 2019. https://itif.org/publications/2019/10/15/robotics-and-future-production-and-work.

Basu, Susanto, and John Fernald. "Information and Communications Technology as a General-Purpose Technology: Evidence from US Industry Data." *German Economic Review* 8, no. 2 (2007): 146–73.

Birse, Ronald M. *Engineering at Edinburgh University: A Short History, 1673-1983*. University of Edinburgh, School of Engineering, 1983.

Breznitz, Dan, and Michael Murphree. *Run of the Red Queen: Government, Innovation, Globalization, and Economic Growth in China*. First Edition first Printing. New Haven Conn.: Yale University Press, 2011.

———. "The Rise of China in Technology Standards: New Norms in Old Institutions." U.S.-China Economic and Security Review Commission, 2013.

Bruland, Kristine. "Industrialisation and Technological Change." In *The Cambridge Economic History of Modern Britain: Volume 1: Industrialisation, 1700–1860*, edited by Paul Johnson and Roderick Floud, 1:117–46. Cambridge: Cambridge University Press, 2004. https://doi.org/10.1017/CHOL9780521820363.006.

Chan, Julian T., Matthew H. Jensen, and Weifeng Zhong. "FEDERAL AGENCIES SHOULD STAY IN THE BACK SEAT FOR AI STANDARD SETTING." *National Institute of Standards and Technology's Request for Information on AI Standards*, May 31, 2019.

Cole, Robert. "Academic Entrepreneurship: A Comparison of U.S. and Japanese Promotion of Information Technology and Computer Science." Center on Japanese Economy and Business Working Paper Series. Columbia Business School, 2013.

David, Paul A. "Some New Standards for the Economics of Standardization in the Information Age." In *Economic Policy and Technological Performance*, edited by Partha Dasgupta and Paul Stoneman, 206–39. Cambridge University Press Cambridge, 1987.

———. "Standardization Policies for Network Technologies: The Flux Between Freedom and Order Revisited." In *Standards, Innovation, and Competitiveness*. Aldershot: Edward Elgar, 1995.

Day, C. R. "The Making of Mechanical Engineers in France: The Ecoles d'Arts et Métiers, 1803-1914." *French Historical Studies* 10, no. 3 (1978): 439–60. https://doi.org/10.2307/286339.

Ding, Jeffrey. "China's Current Capabilities, Policies, and Industrial Ecosystem in AI." U.S.-China Economic and Security Review Commission, June 7, 2019. https://www.uscc.gov/sites/default/files/June%207%20Hearing_Panel%201_Jeffrey%20Ding_China%27s%20Current%20Capabilities%2C%20Policies%2C%20and%20Industrial%20Ecosystem%20in%20AI.pdf.

Edgerton, David. "Innovation, Technology, or History: What Is the Historiography of Technology About." *Technology and Culture* 51, no. 3 (2010): 680–97.

Ernst, Dieter. "Toward Greater Pragmatism? China's Approach to Innovation and Standardization." Institute on Global Conflict and Cooperation, August 2011.

Farnie, Douglas. "Cotton, 1780-1914." In *The Cambridge History of Western Textiles*, edited by David Trevor Jenkins, 1:721–60. Cambridge University Press, 2003.

Fearon, James D., and David D. Laitin. "Integrating Qualitative and Quantitative Methods." In *The Oxford Handbook of Political Science*, 2008.

Frey, Carl Benedikt, and Michael Osborne. "China Won't Win the Race for AI Dominance," October 7, 2020. https://www.foreignaffairs.com/articles/united-states/2020-06-19/china-wont-win-race-ai-dominance.

Fueki, Takuji, and Takuji Kawamoto. "Does Information Technology Raise Japan's Productivity?" *Japan and the World Economy* 21, no. 4 (December 1, 2009): 325–36. https://doi.org/10.1016/j.japwor.2009.02.001.

Godin, Benoît. *Innovation Contested: The Idea of Innovation over the Centuries*. New York; Abingdon: Routledge Taylor & Francis Group, 2015.

Gordon, Robert J. *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*. Princeton University Press, 2016.

Greasley, David, and Les Oxley. "British Industrialization, 1815–1860: A Disaggregate Time-Series Perspective." *Explorations in Economic History* 37, no. 1 (January 1, 2000): 98–119. https://doi.org/10.1006/exeh.1999.0735.

Harley, C. Knick. "British Industrialization Before 1841: Evidence of Slower Growth During the Industrial Revolution." *The Journal of Economic History* 42, no. 2 (1982): 267–89.

Herron, Michael C., and Kevin M. Quinn. "A Careful Look at Modern Case Selection Methods." *Sociological Methods & Research* 45, no. 3 (August 1, 2016): 458–92. https://doi.org/10.1177/0049124114547053.

Inklaar, Robert, and Marcel P. Timmer. "Of Yeast and Mushrooms: Patterns of Industry-Level Productivity Growth." *German Economic Review* 8, no. 2 (2007): 174–87. https://doi.org/10.1111/j.1468-0475.2007.00403.x.

International Federation of Robotics. "IFR Press Conference." Shanghai, September 18, 2019. https://ifr.org/downloads/press2018/IFR%20World%20Robotics%20Presentation%20-%2018%20Sept%202019.pdf.

International Telecommunications Union. "Measuring the Information Society Report 2017," 2017. https://www.itu.int/en/ITU-D/Statistics/Pages/publications/mis2017.aspx.

Jefferys, James. *The Story of the Engineers*. London: Lawrence and Wishart, 1945.

Kannan, Hari, and Christopher Thomas. "Public Cloud in China: Big Challenges, Big Upside | McKinsey." *McKinsey & Company* (blog), July 6, 2018. https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/public-cloud-in-china-big-challenges-big-upside#.

Kennedy, Andrew B. "Powerhouses or Pretenders? Debating China's and India's Emergence as Technological Powers." *The Pacific Review* 28, no. 2 (March 15, 2015): 281–302. https://doi.org/10.1080/09512748.2014.995126.

Kennedy, Andrew B., and Darren J. Lim. "The Innovation Imperative: Technology and US–China Rivalry in the Twenty-First Century." *International Affairs* 94, no. 3 (May 1, 2018): 553–72. https://doi.org/10.1093/ia/iiy044.

Kindleberger, Charles. "Technical Education and the French Entrepreneur." In *Enterprise Andn Entrepreneurs in Nineteenth- and Twentieth-Century France*, edited by E. C. Carter, R. Forster, and J. N. Moody, 3–39. Baltimore, 1976.

King, Gary, Robert O. Keohane, and Sidney Verba. *Designing Social Inquiry: Scientific Inference in Qualitative Research*. Princeton University Press, 1994.

La Bruyère, Emily de, and Nathan Picarsic. "Beijing's Innovation Strategy: Threat-Informed Acquisition for an Era of Great Power Competition." Proceedings of the Seventeenth Annual Acquisition Research Symposium, April 28, 2020.

Landau, Ralph, and Nathan Rosenberg. "Successful Commercialization in the Chemical Process Industries." In *Technology and the Wealth of Nations*, edited by Ralph Landau, David C. Mowery, and Nathan Rosenberg. Stanford: Stanford University Press, 1992.

Langlois, Richard N. "Organizing the Electronic Century." In *The Third Industrial Revolution in Global Business*, edited by Alfonso Gambardella, Giovanni Dosi, Louis Galambos, and Luigi

Orsanigo, 119–67. Comparative Perspectives in Business History. Cambridge: Cambridge University Press, 2013. https://doi.org/10.1017/CBO9781139236706.005.

Luong, Ngor, and Zachary Arnold. "China's Artificial Intelligence Industry Alliance: Understanding China's AI Strategy Through Industry Alliances." Center for Security and Emerging Technology, May 2021.

MacLeod, Christine. *Inventing the Industrial Revolution: The English Patent System, 1660–1800*. Cambridge: Cambridge University Press, 1988. https://doi.org/10.1017/CBO9780511522673.

Mahoney, James, and Gary Goertz. "The Possibility Principle: Choosing Negative Cases in Comparative Research." *The American Political Science Review* 98, no. 4 (2004): 653–69.

Marsden, Ben. "'The Progeny of These Two "Fellows"': Robert Willis, William Whewell and the Sciences of Mechanism, Mechanics and Machinery in Early Victorian Britain." *British Journal for the History of Science* 37, no. 4 (December 2004): 401–34. https://doi.org/10.1017/S0007087404006144.

Mathias, Peter. "Skills and the Diffusion of Innovations from Britain in the Eighteenth Century." *Transactions of the Royal Historical Society* 25 (1975): 93–113. https://doi.org/10.2307/3679088.

———. *The First Industrial Nation: An Economic History of Britain 1700-1914*. London: Methuen, 1969.

McCloskey, Donald N. "The Industrial Revolution, 1780-1860: A Survey." In *The Economic History of Britain since 1700*, edited by Roderick Floud and Donald N. McCloskey. Cambridge; New York: Cambridge University Press, 1981. https://rl.talis.com/3/kent/items/1627B866-67B2-83AF-0F52-1D48D35E7C1B.html.

Meyer, Robinson. "Stanford's Top Major Is Now Computer Science." The Atlantic, June 29, 2012. https://www.theatlantic.com/technology/archive/2012/06/stanfords-top-major-is-now-computer-science/259199/.

Moser, Petra, and Tom Nicholas. "Was Electricity a General Purpose Technology? Evidence from Historical Patent Citations." *The American Economic Review* 94, no. 2 (2004): 388–94.

Musson, Albert Edward, and Eric Robinson. *Science and Technology in the Industrial Revolution*. Taylor & Francis, 1989.

Nakata, Yoshifumi, and Satoru Miyazaki. "The Labor Market for Japanese Scientists and Engineers: Is the Labor Market Externalized? What Has Happened at Their Workplace?" *Japan Labor Review* 8, no. 3 (2011).

National Research Council. *Computing the Future: A Broader Agenda for Computer Science and Engineering*. Washington, D.C.: National Academy Press, 1992.

———. "Funding a Revolution: Government Support for Computing Research." Washington, D.C, 1999.

Naughton, Barry J. *The Chinese Economy, Second Edition: Adaptation and Growth*. Second edition. Cambridge, Massachusetts: The MIT Press, 2018.

Newell, Allen. "Introduction to the COMTEX Microfiche Edition of Reports on Artificial Intelligence from Carnegie-Mellon University." *AI Magazine*, September 15, 1984.

Oliner, Stephen D., and Daniel E. Sichel. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" *Journal of Economic Perspectives* 14, no. 4 (December 2000): 3–22. https://doi.org/10.1257/jep.14.4.3.

Ostry, Sylvia, and Richard R. Nelson. *Techno-Nationalism and Techno-Globalism: Conflict and Cooperation*. Washington, D.C: Brookings Institution Press, 1995.

Petralia, Sergio. "GPTs and Growth: Evidence on the Technological Adoption of Electrical and Electronic Technologies in the 1920s." *European Review of Economic History*, no. heaa022 (November 24, 2020). https://doi.org/10.1093/erehj/heaa022.

———. "Mapping General Purpose Technologies with Patent Data." *Research Policy* 49, no. 7 (September 1, 2020): 104013. https://doi.org/10.1016/j.respol.2020.104013.

Pollard, Sidney. *The Genesis of Modern Management: A Study of the Industrial Revolution in Great Britain*. First Edition. Cambridge, MA: Harvard University Press, 1965.
Porter, Michael E. *The Competitive Advantage of Nations*. New York: Free Press, 1990.
Rapkin, David, and William Thompson. "Power Transition, Challenge and the (Re)Emergence of China." *International Interactions* 29, no. 4 (October 1, 2003): 315–42. https://doi.org/10.1080/714950652.
Rohlfing, Ingo, and Carsten Q. Schneider. "Improving Research On Necessary Conditions: Formalized Case Selection for Process Tracing after QCA." *Political Research Quarterly* 66, no. 1 (2013): 220–35.
SCMP Research. "China AI Report 2020," February 2020.
Steinmueller, W. Edward. "The U.S. Software Industry: An Analysis and Interpretive History." In *The International Computer Software Industry: A Comparative Study of Industry Evolution and Structure*, edited by David C. Mowery, 15–52. New York: Oxford University Press, 1996.
Synced [机器之心]. "Market Research Report on Supply and Demand for Digital Intelligentization Solutions for China's Small and Medium Enterprises [中国中小企业数智化解决方案供应市场研究报告2020]," October 2020.
Tagscherer, Ulrike. "Science-Industry-Linkages in China: Motivation, Models and Success Factors for Collaborations of MNCs with Chinese Academia." *Discussion Papers "Innovation Systems and Policy Analysis."* Discussion Papers "Innovation Systems and Policy Analysis." Fraunhofer Institute for Systems and Innovation Research (ISI), 2015. https://ideas.repec.org/p/zbw/fisidp/47.html.
Techxcope [战略前沿技术]. "Innovation Is More than Invention: Detailed Explanation of the German Industry-University-Research Systems' Big Four [创新不止于发明：德国产学研体系四大金刚详解]," November 18, 2020.
Tellis, Ashley J. "Balancing without Containment: A U.S. Strategy for Confronting China's Rise." *The Washington Quarterly* 36, no. 4 (October 1, 2013): 109–24. https://doi.org/10.1080/0163660X.2013.861717.
Temin, Peter. "Two Views of the British Industrial Revolution." *The Journal of Economic History* 57, no. 1 (1997): 63–82.
Tomory, Leslie. "Technology in the British Industrial Revolution." *History Compass* 14, no. 4 (2016): 152–67. https://doi.org/10.1111/hic3.12306.
Vona, Francesco, and Davide Consoli. "Innovation and Skill Dynamics: A Life-Cycle Approach." *Industrial and Corporate Change* 24, no. 6 (2014): 1393–1415. https://doi.org/10.1093/icc/dtu028.
Wang, Ping, and Liang Zheng. "Beyond Government Control of China's Standardization System — History, Current Status, and Reform Suggestions." In *Megaregionalism 2.0*, edited by Dieter Ernst and Michael Plummer, 311–39. World Scientific, 2018. https://ideas.repec.org/h/wsi/wschap/9789813229839_0015.html.
Wirkierman, Ariel Luis. "Yeasty vs. Mushroom-like Patterns of Hyper-Integrated Productivity Growth: An Analysis of Six Advanced Industrial Economies," 2014.
Yates, JoAnne, and Craig N. Murphy. *Engineering Rules: Global Standard Setting since 1880*. JHU Press, 2019.

Zhang, Daniel, Saurabh Mishra, Erik Brynjolfsson, John Etchemendy, Deep Ganguli, Barbara Grosz, Terah Lyons, et al. "The AI Index 2021 Annual Report." Human-Centered Artificial Intelligence Institute, 2021.