What factors led to the trade war between the US and China, and what are their implications for technological competition, specifically artificial intelligence (AI), between the two countries?

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Abstract

The economic rise of China has had a profound impact on the global economy. As Chinese products have become competitive in global markets, manufacturing in advanced economies, such as the US, has faced challenges. These economic transformations have led to different political reactions, namely, America's initiation of the trade war against China in 2018. In this paper, I study what factors led to the trade war between the US and China, and what their implications are for the technological competition, specifically on artificial intelligence (AI), between the two countries. The first section focuses on the factors that led to the trade war and analyzes them through the lens of trade theories in economics - Ricardo and Heckscher-Ohlin models. The second section then investigates the implications of the trade war for technological competition between the two countries, particularly on AI. While the US still takes the lead in AI technology, China is catching up quite rapidly. Competition in AI has implications for national security and for the semiconductor industry. As the economic rise of China can explain the US-China trade war, China's advance in AI may lead to further technological competition between the two countries.

Introduction

When two of the world's superpowers begin to clash, major changes are bound to occur as their conflict leaves shockwaves around the globe. The United States and China, respectively, boast the first and second largest economies worldwide in addition to possessing superior political, technological, and military might. However, their recent relationship has been rocky at best, especially since China's rise in the 2000s. Such strain on the US-China relationship is particularly evident when looking at the two countries' economic interactions and the US-China trade war that resulted from it.

This paper aims to uncover what factors led to the trade war and what implications they may have in the domain of technological competition, in particular on artificial intelligence (AI), between the two countries. My interest in US-China relations stems largely from my heritage. As an ABC, or American-born Chinese, raised in the US by Chinese parents who taught me to embrace my heritage while being surrounded by American culture, the topic of how the two halves of my cultural background interacted with each other has always fascinated me. The focus of the investigation on the US-China trade war is a result of my keen interest in economics, in which China's rise during the 2000s played a key role. My father works in finance, and I grew up constantly hearing news about China's economic rise. As I began to pay attention to economics and economic news, I was surprised by how much of it was centered around China.

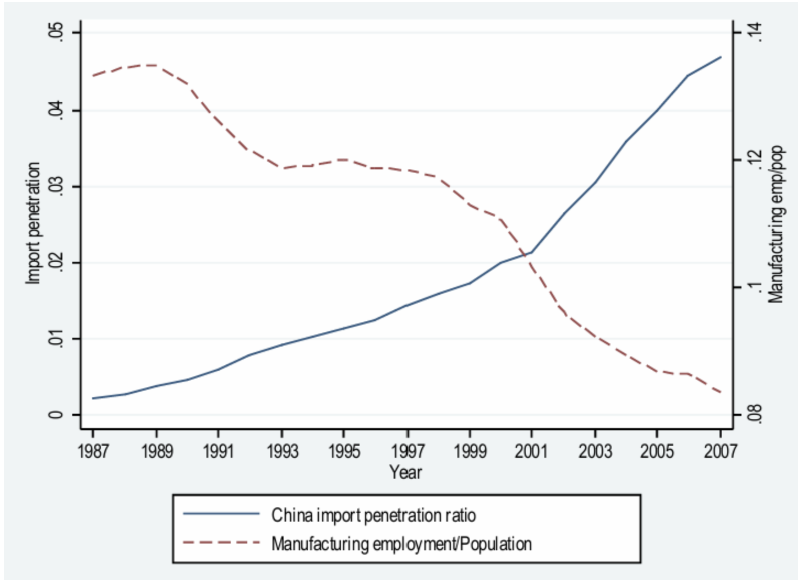
These personal and academic interests culminated in the research question: What factors led to the trade war between the US and China, and what are their implications for technological competition, particularly on AI, between the two countries? This paper aims to answer these questions. The first section will study the factors that led to the trade war using the lens of trade theories in economics – Ricardo and Heckscher-Ohlin models, and the second section will investigate the implications of those factors for the technological competition between the US and China, particularly in AI.

Overview of the US-China Trade War

Since the economic reforms in 1979, China has gained competitiveness in many industries, particularly in low-cost manufacturing. When China joined the WTO in 2001, it became even more competitive in these sectors than before. David Autor, David Dorn, and Gordon H. Hanson (2013) study how an increase in Chinese competitiveness in low-cost manufacturing led to a decrease in US employment in that sector. Specifically, their paper studies the effect of Chinese import penetration into the US on its labor market.

They first establish that there is a strong correlation between Chinese import penetration into the US and the decline in US manufacturing labor share. Figure 1 plots the Chinese import penetration ratio and US manufacturing employment from 1987 to 2007. The share of goods imported from China is in blue, and the share of US employment in manufacturing is in red (dashed line). The clear trend is that as Chinese import penetration increased, US manufacturing employment share decreased over time. The Chinese import penetration ratio increased from around 0.2% in 1987 to around 4.6% in 2007, while the US manufacturing employment share decreased from around 13% in 1987 to around 8% in 2007. One conclusion that can be drawn from this trend is that imports from China could potentially explain the decrease in US manufacturing employment.

Figure 1: Chinese import penetration ratio and US manufacturing employment share



Source: Autor, Dorn, and Hanson (2013). Chinese import penetration ratio is in blue and the scale is on the left axis. US manufacturing employment share is in red (dashed line) and the scale is on the right axis.

They examine commuting-zone-level data on Chinese import penetration and US manufacturing employment share. Using regression techniques, which can be understood as a line of best fit, the authors find that Chinese import penetration can causally explain the decline in US manufacturing employment share. This effect is most pronounced in the Midwestern regions, which used to be America's largest manufacturing centers.

One can interpret these findings through the lens of trade theories in economics - Ricardo and Heckscher-Ohlin models. When countries trade, it means that rather than producing all the goods they consume domestically, they specialize in producing some goods (which they export) and import other goods. The Ricardo model predicts that countries produce goods in which they have comparative advantage, meaning that they produce goods for which they are relatively better at producing than other countries (Krugman, Obstfeld, and Melitz, 2022).

To illustrate this concept more concretely, consider a simplified and hypothetical two-country, two-good example as follows: assume that the US and China produce clothing and semiconductors. Suppose that America's productivity is 2 for clothing and 10 for semiconductors, while China's productivity is 1 and 2, respectively. Even though the US is better than China in producing both clothing and semiconductors (meaning the US has an absolute advantage over China in producing both goods), China has a comparative advantage over the US in producing clothing. The reason is that the ratio of the productivity of clothing to semiconductors is 2/10 = 0.2 for the US, while it is 1/2 = 0.5 for China. According to the Ricardo model, China will export clothing to the US, while the US will export semiconductors to China.

On the other hand, the Heckscher-Ohlin model dictates that a country will export goods that are intensive in the factor with which the country is abundant. Continuing with the previous example of the US and China producing clothing and semiconductors, now additionally include the fact that clothing is labor-intensive while semiconductors are capital-intensive. Considering that the US is abundant in capital while China is abundant in labor, the Heckscher-Ohlin model suggests that China will export clothing to the US because clothing is labor-intensive and China is abundant in labor, while the US will export semiconductors to China because semiconductors are capital-intensive and the US is abundant in capital.

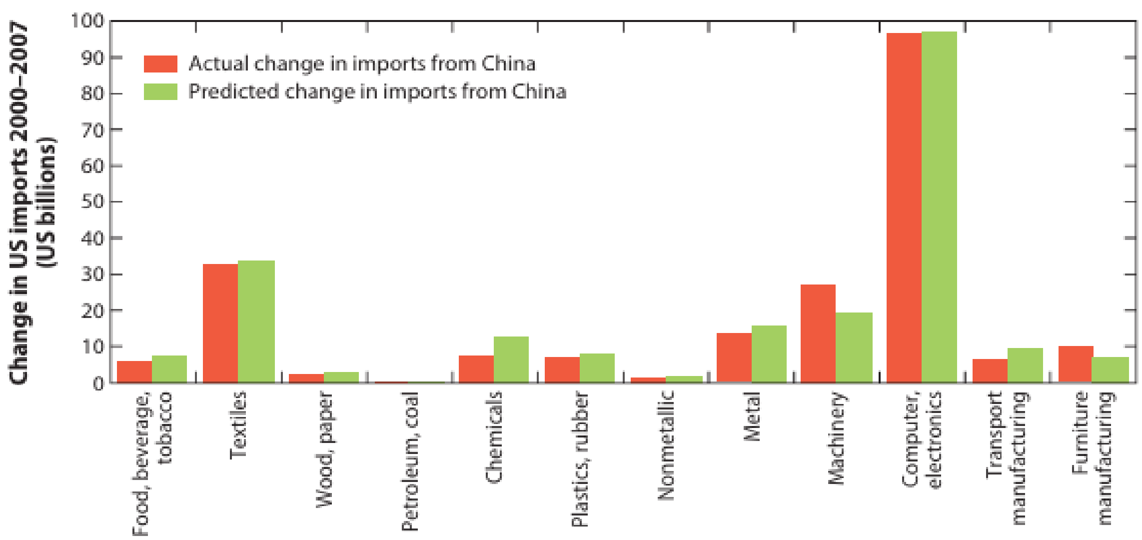
Further research by Autor, Dorn, and Hanson in collaboration with Kaveh Majlesi (2020) investigates to what extent the economic rise of China and the consequent decline in US manufacturing can explain the change in the political environment in the US and how that change can explain the factors that led to the trade war. Their research utilizes regional election data and studies not only the divisive 2016 presidential election, but also the 2000 and 2008 presidential elections, as well as the 2002 and 2010 congressional elections. They find strong evidence that regions exposed to larger increases in import penetration leaned more republican in their votes. Midwestern states like Michigan, Pennsylvania, and Wisconsin, which all had high Chinese import penetration, played key roles in the 2016 presidential election.

These factors of China's rapid economic growth and penetration into US-dominated markets culminated in the US-China trade war. The trade war unfolded over a series of tariff waves between 2018 and 2019. The first wave of tariffs consisted of US safeguard tariffs targeted at specific products manufactured by different countries, including China. In response, China and other countries passed retaliatory tariffs, but subsequent tariff waves were largely held between the US and China, becoming known as the trade war. By 2019, the tariffs had already amounted to around $350 billion worth of Chinese imports and $100 billion of US exports, lowering US real income by about 0.1% of its GDP. China's loss was more substantial, however, as its real income was lowered by around 0.29% of its GDP.

Pablo Fajgelbaum and Amit Khandelwal (2022) study the effect of tariffs that have resulted from the trade war on consumers. One useful metric to gauge the effect of tariffs is pass-through, which measures by what percentage points consumer prices increase in response to a one percentage point increase in tariffs. The authors find that there have been observations of a virtually complete tariff pass-through in the US. Having a near-complete tariff pass-through is surprising because it goes against the large amount of prior literature and research supporting incomplete tariff pass-through. These observations imply that US buyers of imports bore the full brunt of Chinese tariffs without any significant price adjustments from Chinese exporters and that the tariffs functioned as a direct tax on American consumers, reducing their purchasing power. The near-complete tariff pass-through and lack of price adjustments from China also highlight the difficulty of using tariffs to improve trade terms or gain leverage in negotiations.

Zooming out from the US-China trade war to study the trade relations between the two countries over the past two decades, Lorenzo Caliendo and Fernando Parro (2023) start their discussion with the "China shock," which refers to the increase in Chinese manufacturing productivity when China joined the WTO in 2001. They measure and analyze the effect of the China shock on the bilateral trade deficit of the US against China. Though the newly integrated US-China economic relationship created aggregate gains, bringing overall economic benefits, the gains were distributed unevenly, impacting each sector and region differently, creating winners and losers. They also found that the expansion of trade in China was not the primary cause of the US decline in manufacturing employment. Instead, they argue that the main cause was the decline in US manufacturing productivity due to the increase in labor costs. Figure 2 shows that, though there is variation across all kinds of trade sectors, the sector with the most exposure is computers and electronics. This large amount of exposure from the computers and electronics sector of US manufacturing has great implications for the future of US-China technological competitiveness, especially with AI, which will be further explored in the next section.

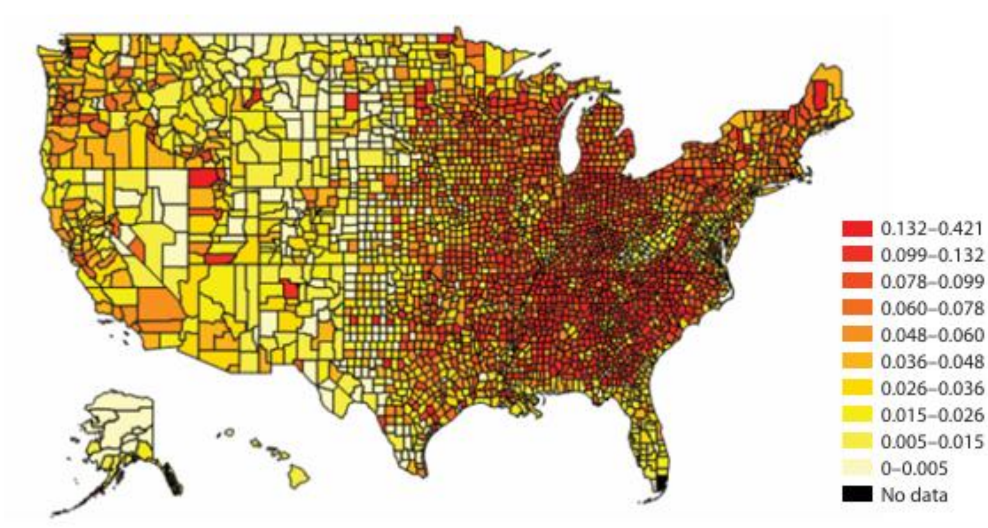
Figure 2: Predicted vs. actual changes in manufacturing imports from China



Source: Caliendo Parro (2023). Changes are measured in billions of US dollars, 2000-2007.

With the effects of the China shock in mind, they then focus on the US-China trade war of 2018, where their main findings include how the trade war generated welfare losses, had small employment effects, and was ineffective in reversing the distributional effects. The two authors used the Normal Trade Relations (NTR) gap to measure how the gains and losses from the US-China trade war were distributed across different regions of the US. NTR refers to the tariff rate before the trade war, and NTR gap refers to the difference in the tariff rate before and after the trade war. Figure 3 provides a map of the US, color-coded by NTR gap. As Figure 3 suggests, what they found was that the regions with a higher composition of manufacturing, such as Michigan, Wisconsin, and Pennsylvania, experienced net gains, while other regions experienced net losses. Caliendo and Parro reason that since the China shock was not a primary cause of the decline in US manufacturing employment, the trade war would not be an effective way to address it.

Figure 3: NTR gap across America at the county level



Source: Caliendo Parro (2023). Gaps are measured using employment shares in 1990. The color scale represents percentiles.

Implications of Technological Competition, particularly on AI

So far, I have only examined the relationship between the US and China in the domain of trade. This section will, by contrast, focus on the relationship between the two countries in the domain of technological competition, particularly on AI, and investigate whether implications from the domain of trade can also be applied to the domain of technology.

Avi Goldfarb and Daniel Trefler (2019) look at how the growth of artificial intelligence (AI) has reshaped the global economy and use theories from international trade to understand the strategies and policies of governments in the field of AI. They start by examining the growth of AI through the statistical analysis of the composition of countries attending major AI conferences and the AI exposure of the world's most valuable companies. Figures 4 and 5, respectively, provide this data.

Figure 4: Participants by country at a major AI conference.

Participants at a major AI conference

Country	2012 (%)	2017 (%)	Change (%)
United States	41	34	–6
China	10	23	13
United Kingdom	5	5	0
Singapore	2	4	2
Japan	3	4	1
Australia	6	3	–2
Canada	5	3	–3
India	1	2	1
Hong Kong	3	2	–1
Germany	4	2	–1
France	4	2	–2
Israel	4	2	–3
Italy	2	2	–1
Other	10	10	0

Source: Goldfarb Trefler (2019). Participation rates at the Association for the Advancement of Artificial Intelligence (AAAI) Conference on AI. Of the papers presented at the 2017 conference, 34 percent were of US affiliation.

Figure 5: The World's largest public companies and their amount of AI exposure.

World's largest public companies and AI exposure

Company	Market value ($)	AI exposure
1. Apple	754	High
2. Alphabet	579	High
3. Microsoft	509	High
4. Amazon	423	High
5. Berkshire Hathaway	411	Rising
6. Facebook	411	High
7. ExxonMobil	340	Low
8. Johnson & Johnson	338	Rising
9. JPMorgan Chase	314	Rising
10. Wells Fargo	279	Rising
11. Tencent Holdings	272	High
12. Alibaba	269	High

Source: Goldfarb Trefler (2019). Market capitalization of the largest publicly traded companies as of March 2017. "AI Exposure" refers to the subjective assessment of AI's role in company performance.

Applying economic theories such as economies of scale and knowledge diffusion, Goldfarb and Trefler suggest that international cooperation in the realm of AI may lead to overall aggregate gains. For industries that require large initial investments, increasing the scale of their operations could lower the marginal cost. AI is an industry that requires huge initial investments because of the cost of supercomputers and engineers needed to collect data to increase the scale of operations further. International cooperation may help increase the general size of operations, thereby lowering the marginal cost. The spillover of knowledge is also crucial to achieving advancements in AI, but it can also challenge equitable international distribution.

Knowledge diffusion, on the other hand, refers to the spread of knowledge throughout people and across regions over time. Goldfarb and Trefler note that expertise in the field of AI seems to be geographically clustered. AI knowledge tends to gather in key regions such as Silicon Valley, Beijing, Shanghai, or London. These knowledge hubs greatly benefit from agglomeration effects, where the proximity of such knowledge facilitates collaboration and innovation. The existence of such hubs suggests that AI involves a large amount of localized and tacit knowledge; knowledge that is harder to transfer because it often necessitates close collaboration or geographic proximity.

Surprisingly, AI expertise is centered around universities that are involved in AI advancement. Many technology firms are setting up around such universities to access their talent. Google DeepMind, for instance, is based in London because of its researchers' affiliation with University College London. The field of AI has led to significant amounts of knowledge spillover, mostly on the subnational scale, which naturally promotes the idea of regional knowledge clusters that drive rapid innovation and collaboration. However, there are two primary inhibitors to knowledge diffusion: language/cultural barriers and legal/regulatory barriers. Language proficiency affects the transfer of knowledge between regions, especially between English-speaking countries and non-English-speaking hubs. Variations in data privacy laws, regulations, and intellectual property laws influence the degree to which AI knowledge can be freely spread across nations.

AI has become a new arena for international competition because of its profound impacts on social and economic development. Countries around the world have begun to attach great importance to the development of AI. China and the US were among the first to recognize AI as a field with implications for economic growth, national security, and global power dynamics, marking it as an essential tool for future industrial and military leadership, and have since poured vast amounts of resources into growing it.

Competition between the U.S. and China is gradually increasing due to broader geopolitical tensions, such as trade disputes and targeted restrictions on technology transfers. The AI development race has become a main field of competition in the already heated US-China rivalry. For a more detailed look into the technological competition between the two leaders in AI development, I will rely on the expertise of You Wang and Dingding Chen (2018). The two countries employ unique strategies for AI expansion but have differing gaps in their AI capabilities. The U.S. enjoys a 'first mover advantage' and is far ahead of China in terms of AI theory, microchips, cutting-edge AI research, and talent pools. It also boasts a superior industrial structure, business environment, and distribution. Most of the world's tech giants (Google, Amazon, IBM, Microsoft) are all based in the U.S. and possess some of the best AI research teams in the world. Additionally, nearly all the best AI/computer science universities in the world (MIT, UC Berkeley, GA Tech, Stanford, Carnegie Mellon) are all located in the U.S.

Due to these strengths, the U.S. approach to AI strategies is decentralized innovation, promoting collaboration between academia, industry, and government. Though China lags behind the US in terms of fundamental research, industrial depth, and AI talent, it is rapidly catching up with support from strong government initiatives and growing industrial investments. China has made great efforts to expand AI R&D (research and development) to close the gap between them and the U.S. Despite this rapid growth, the country and its AI industry suffer from a serious lack of technological talent because most of it is concentrated within the regional AI knowledge clusters located largely monopolized by the US. The Chinese approach is more top-down, with government-led policies and investments focused on driving AI development to compensate for its lack of AI talent and academia.

Since AI is not a specific weapon, but rather akin to a general-purpose technology that has broad implications across industries and can significantly influence the balance of power, it is applicable both in a civilian and military context, which accelerates its global spread. The potential effects of AI on military technology and competition are huge. AI could allow for the enhancement of military logistics, decision-making, and autonomous systems, all of which could drastically change the speed and strategy of modern warfare. Countries that are able to rapidly adopt and incorporate AI in military contexts gain strategic 'first-mover' advantages, though those advantages may be limited due to the rapid diffusion of AI knowledge. Nevertheless, properly adopting AI into military contexts would require overcoming major challenges, including the development of trust and reliability in autonomous systems, training personnel in new skills required to operate or understand AI technology, and aligning military innovation with technological advancements. The race for AI development has been increasingly described as more of an arms race between nations like the US, China, and Russia. Horowitz (2018) concludes that should major world forces fail to adapt to AI or if lesser ones use AI in a cost-effective way to empower themselves, the balance of world power is subject to massive shifts.

Semiconductors from the Lens of the AI Boom

As previously discussed, one of the main issues in AI advancement is the vast computational power and storage space needed to develop and implement new algorithms. Consequently, demand for semiconductors skyrocketed, and the semiconductor industry thus holds the key to AI. In this section, I analyze how the semiconductor industry has transformed in the last decade and what its implications are for AI.

Henry Wai-chung Yeung provides an overview of the recent developments and geographical shifts in the semiconductor industry in his 2022 paper. During the last two decades, the semiconductor industry has changed such that there are two different types of chips. The first type is memory semiconductors, which are used for storage, and the second type is system semiconductors, which specialize in computation. For the memory division, all semiconductors are designed and manufactured by the same firms, and the key producers of these chips include Samsung Electronics, SK Hynix, and Micron. Of these key producers, the first two are based in South Korea, while the latter is based in the US. For the system division, design and manufacturing are done by separate firms. The firms that focus on designing the most advanced system chips include Nvidia and AI firms such as Apple and Alphabet. These firms outsource the manufacturing of their chips, which is referred to as foundry. The leading figure in semiconductor foundry is the Taiwan Semiconductor Manufacturing Company (TSMC).

Evidenced by companies like Samsung and SK Hynix leading the memory division and TSMC leading the system division, semiconductor production has transitioned to be largely based around countries in East Asia, excluding Japan, from originally being centered around the US, Japan, and Western Europe. Figure 6 shows the headquarters and fab locations of the world's leading semiconductor manufacturers in 2010 and 2018. The geographical transition of the semiconductor industry has numerous implications for the US-China competition in AI. While US firms still dominate the design of system semiconductors, production of memory and system chips is dominated by firms based in Taiwan and South Korea. Although these two countries are US allies, their physical proximity to China is a key consideration for policymakers in the US.

Figure 6: Top Semiconductor Manufacturers, the locations of their headquarters and fabs

World's Top Semiconductor Manufacturers by Fab Capacity, Main Applications, Fab Locations, and Markets, 2010 and 2018

Lead Firms	Sales ($b) 2010	Sales ($b) 2018	Fab capacity[1]	Applications (% of 2018 sales)	Location of HQs and Fabs	Key End-market Segment (% of 2018 sales)
IDM						
Samsung	28.4	74.6	2,474	Memory 88%	South Korea, US, China	Smartphones, PCs, consumer electronics
Intel	40.4	69.9	722	Microprocessors 76%	US, Ireland, Israel, China	PCs, servers, and data centers
SK Hynix	10.4	36.3	1,385	Memory 99%	South Korea, China	Smartphones and PCs
Micron	8.9	29.7	1,038	Memory 100%	US, Singapore, Taiwan, Japan	PCs, servers 37%, storage 26%, smartphones 21%
Toshiba	13.0	11.4	1,310	Memory 100%	Japan	Smartphones, PCs, consumer electronics
Foundry						
TSMC	12.9	31.1	2,266	Logic 87%	Taiwan, China, US	Smartphones 54%, PCs 15%, industrial electronics 17%
GlobalFoundries	3.5	6.2	592	Logic 68%	US, Germany, Singapore	Smartphones 35%, PCs 23%, consumer electronics 23%
UMC	3.8	5.0	653	Logic 84%	Taiwan, China, Singapore	Smartphones 42%, PCs 16%, consumer electronics 28%
Samsung	0.8	3.4	371	Logic 100%	South Korea, US	Smartphones and PCs
SMIC	1.6	3.0	451	Logic 53%	China	Smartphones and wireless 41%, consumer electronics 38%
World market	312	485	16,997	Memory 34% Logic 22% Microprocessors 12%	-	Computer & data storage 37% Wireless and smartphones 30% Industrial electronics 11% Consumer electronics 8.6%

Source: Yeung (2022).

Yeung collaborated further with Shaopeng Huang and Yuqing Xing to explore more transformations in the semiconductor industry by looking at current trends in the semiconductor global value chain (GVC). In the past, the integrated device manufacturing (IDM) model, where large American semiconductor firms aimed to control all aspects of chip production, from design to manufacturing, was the conventional method of production. However, the high costs associated with building and maintaining fabrication plants (fabs) led to the rise of 'fabless' semiconductor firms that specialized in design while outsourcing manufacturing tasks to third-party foundries. Since the 1980s, these fabless firms have been slowly dominating the semiconductor manufacturing industry. The fabless revolution has geographically concentrated semiconductor manufacturing in East Asia, particularly in Taiwan, South Korea, China, and Singapore, where

80% of the world's electronic wafer fabrication capacity was located between 2018 and 2023. The dominance of East Asian manufacturers, like TSMC, has raised concerns among governments about semiconductor supply chain security, particularly in light of geopolitical tensions and disruptions caused by the COVID-19 pandemic. In response, major economies, including China and the US, have introduced industrial policies to increase domestic semiconductor manufacturing capabilities, including large-scale subsidies, tax incentives, and national investment programs aimed at reducing the reliance on foreign semiconductor supply chains.

Conclusion

This paper explored the key drivers behind the US-China trade war and its far-reaching implications for future technological competition, especially in the realm of Artificial Intelligence (AI), between the two countries. The first section outlined the origins of the US-China trade war, tracing it to China's ascension to the WTO in 2001 and the ensuing 'China shock' that reshaped American manufacturing. The increase in Chinese competitiveness in low-cost manufacturing led to a decrease in American competitiveness in that sector, and consequently in US manufacturing employment. In the second section, I examined beyond trade, looking into how the rivalry between the US and China has extended into the strategic domain of AI, where both nations view technological supremacy as critical to national power.

While the US maintains its "first mover advantage," keeping an edge in AI innovation and talent, China's state-driven investment model has enabled it to close the gap in its AI capabilities rapidly. As China limits the US from entering its markets with protectionist policies, it has leveraged those same policies to develop strong domestic AI companies (Baidu, Alibaba, Tencent) and compete with large American companies like Google and Amazon. AI will likely increase incomes and improve well-being, but it continues to raise concerns about the shifting of global power balances.

As research and development in AI require serious storage and computing power, semiconductors play a key role in the development of AI. This geographical shift in semiconductor production to East Asia, particularly to countries like South Korea and Taiwan, has strategic implications for AI development, given their proximity to China and importance as US allies.

From an analysis of the US-China trade war, we see that it has caused more harm than good for the US economy. Fajgelbaum and Khandelwal (2022) find a virtually complete tariff pass-through, meaning that US consumers bore the full brunt of tariffs on Chinese imports without any significant price adjustments by Chinese exporters. Caliendo and Parro (2023), in addition, find that the main cause of the decline in US manufacturing employment was not the China shock but the decline in US manufacturing productivity, proving that the trade war was not an effective policy to recover US manufacturing jobs.

One implication of the US-China trade war on technological competition between the two superpowers is that, rather than hostile competition, a more cooperative approach in the field of AI may be more aligned with US national interests. With most AI expertise being clustered in specific regions like Beijing and Silicon Valley, it involves a large amount of localized knowledge that is difficult to pass on to other regions due to the need for close collaboration or geographical proximity. For AI to improve further through research and development, it is crucial to create knowledge spillover that is not strictly limited to the subnational scale.

Another implication of the US-China trade war is the importance of allies. During the trade war, the US imposed tariffs and non-tariff barriers not only against China but also against US allies, including the European Union, Japan, and South Korea. If the US had enacted a more constructive approach and cooperated with its allies, changes in trade policies may have had a more positive effect on the US. Relating to technological competition, if the US cooperates with its allies, this may contribute to the US maintaining and further advancing its strategic advantage over China. Especially with the key role semiconductors play in the development of AI, the geographical shift of semiconductor manufacturing to the region of East Asia may prove to be a vital tool to the US and its alliance with countries like South Korea and Taiwan, which house a large number of semiconductor production firm HQs and fabs.

Considering AI's potential applications in the military, AI is no longer merely a technological advancement, but is increasingly becoming a strategic asset that nations around the world are using to help shape their global influence. As the race for technological prowess continues to shape the global order, the US must reassess how it balances competition with cooperation. In this new age where technological leadership equates to geopolitical power, the outcome of this balancing act will shape not just the global balance of power but also the future of innovation itself.

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