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论文题目：**China Trade Shock Does Not Hurt U.S. Innovation**

# China Trade Shock Does Not Hurt U.S. Innovation

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Abstract

A vast literature documents the impact of the so-called “China Trade Shock”, that is, the spectacular growth in Chinese export to the rest of the world since joining WTO in 2001. Notably, Autor et al. (2020) show that increased imports from China hurt the innovation of U.S. domestic firms. However, some recent literature suggests that the majority of the “China Trade Shock” studies fail to account for the effect on upstream industries, which could have a positive impact. Using this supply-chain perspective, I re-examine the results in Autor et al. (2020) and find that the “China Trade Shock” on upstream industries has a strong and significant positive effect on U.S. firms' innovation in terms of patenting activities. Furthermore, the positive effect almost fully offsets the negative effect, thus over-turning the finding claimed by Autor et al. (2020). My research provides a cautionary tale that the negative impacts of the “China Trade Shock” may have been overstated.

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## 1. *Introduction*

After entering the WTO in 2001 with the assistance of social reforms in the 1990s (Naughton 2007), China experienced astonishing growth in international trade and particularly export to developed countries. This phenomenon is dubbed the "China Trade shock" and has drawn a lot of attention from scholars in the field of economics. Autor et al. (2013) is a pioneering work in this area and finds substantial negative impacts of Chinese export on the exposed local labor market in the United States. Autor et al. (2020) have revealed the impact of direct Chinese import penetration on US industries' sales, profitability, R&D expenditure, and patent production. In terms of innovation, Aghion et al. (2017) examine the impact of Chinese exports on French firms. They find a generally positive impact on high-productivity firms' innovation outcomes, while low-productivity firms may be negatively affected. More recently, Aghion et al. (2021) develop a broader investigation and consider not only the horizontal shock experienced by firms that are directly competing with Chinese exporting firms, but also the vertical impact experienced by firms that use inputs that are also subject to increased Chinese exports. In addition to confirming the direct and negative effects on a firm's innovation outcomes, they also find a potential positive upstream effect in French firms, though this effect is not statistically significant.

Relatedly, Wang et al. (2018) re-examine the local employment impacts in the U.S. and utilize a supply-chain perspective that also takes into account not just the direct effect, but also the upstream effect. They find that the overall impact of Chinese import competition is positive, i.e., it boosts local employment, in contrast to the findings of Autor et al. (2003). The overall positive effect is mainly due to a considerable positive impact of upstream exposure that outcompetes the combined negative effect of direct and downstream channels. This positive effect could arise from cheaper raw materials and inputs in the upstream industries due to competition from Chinese exports, which foster the downstream firm's growth. In the end, trade with China creates local employment, and the American workers on average experience a rise in real wages.

This paper aims to use a similar supply-chain perspective to evaluate the impact of Chinese import competition on US firms' innovation outcomes, which is missing from the existing literature. Notable works such as Autor et al. (2020), did not take channels other than direct exposure into account. Aghion et al. (2021) use the sample of French firms and examine the impact of the upstream channel but did not find significant results. Our reasoning is as follows: from the upstream perspective, firms could experience cheaper and higher quality inputs due to increased China Shock, hence stimulating their innovative investments. Despite that U.S. firms could have faced tougher competition from China in their output industries, they could also have enjoyed benefits due to the Chinese competition in the upstream or input industries. The overall impact on U.S. firms' innovation outcomes, taking into account both the negative direct effects and potentially positive upstream effects, is therefore an empirical question.

By using the Input/Output (IO) table from the U.S. Census Bureau that provides a record of detailed uses of inputs and outputs for a given industry, we are able to identify the upstream China Trade Shock facing a given industry. More specifically, according to each industry's input share, we construct the upstream channel by aggregating the direct exposure of each input industry to the China Trade Shock. For a downstream channel, we did the opposite, looking at the output/sales of each industry. After assigning the China shock to each output industry, we compute the sales-weighted average of the direct competition exposure of all of an industry's customers. We are therefore also able to control for the effect of China Trade Shock facing the downstream industries of a given focal industry.

In our empirical analysis, we discover a statistically significant positive and offsetting effect from the upstream channel. We confirm that our results are consistent with existing literature, that direct trade exposure significantly reduces U.S. firms' patent production. We discover a positive and significant effect in the upstream channel. In terms of economic magnitude, the upstream channel effectively offsets most of the innovation lost due to direct exposure. The downstream channel reinforces the negative impact, although insignificantly. In summary, we conclude that trade with China does not reduce U.S. innovation levels on average, thus casting doubts on the results in Autor et al. (2020). We also assess the extent to which the firms' patent production is affected based on four characteristics: productivity, capital intensity, profitability, and leverage. In some indicators, we discover a similar pattern, where the upstream channel produces a positive impact on patent production that counterbalances the negative impact from the direct channel. However, we find some dominating impacts in the direct channel for other indicators.

The initial seminal work of Autor et al. (2013) primarily focuses on the impact on the US labor market after facing intensified import competition from China. The study has shown that this import competition has contributed to one-quarter of the decline in US manufacturing employment. Another study by Autor et al. (2013) reinforces such impact by highlighting the unequal distribution of labor costs after being impacted by the “China trade shock.” It is shown that those who initially had lower wages than average eventually experienced more significant earnings loss, while the high-wage workers found it easier to change jobs with minimal losses or stay in their current positions.

After Autor et al. (2013), a vast literature focuses on US employment affected by trade with China, the study done by Pierce and Schott (2016) reinforces such adverse effects by carrying out an empirical analysis that looks at how the eliminated potential tariff increase uncertainty on Chinese imports have induced employment loss in the US. Notably, Pierce and Schott (2016) consider not only the directly exposed manufacturing industries but also their upstream (suppliers) & downstream (buyers) industries. Such linkages would have two effects on manufacturing employment. On the one hand, import competition may cause an industry to be worse off, which would lead to a reduction in demand for inputs produced in other industries (upstream) and a decline in the supply of inputs to the other industries (downstream). Hence, there are two ways for industries to indirectly and negatively affected other industries by the “China trade shock” -domestic suppliers or domestic buyers. The impact of the “upstream effect,” through which an affected industry may affect its buying industries, is undetermined since the reduced supply of domestic firms may be offset by the increased supply of Chinese industry. However, the “downstream effect” impact is relatively straightforward- a decline in the industry's performance would similarly affect its suppliers. We use a similar input-output linkage to construct our upstream and downstream channels in our analysis.

In terms of employment opportunities, Acemoglu et al. (2016) apply two empirical approaches by considering the entire economy through the lens of input-output linkage and other important offsetting channels (reallocation effect and aggregate demand effect). Their study supports their estimation that Chinese import penetration is a significant force behind the reduction of employment in the U.S. Moreover, the inter-industry measure increases the size of unemployment in the entire economy, doubling the size of the impact.

However, when Wang et al. (2018) re-examine the effect of China imports on the US local labor market using a supply chain perspective, similar to the input-output linkage, the results showed that the impact of trading with China as a whole has an overall positive effect on local employment and real wages. Interestingly, the paper points out that the most beneficial factor to local employment is job creation other than the manufacturing sector through the downstream channel.

Moreover, despite labor markets, scholars have been interested in the innovation levels of firms affected by trade. It is commonly accepted that R&D development is crucial to a firm's long-term growth. However, there is evidence that investments from those leading firms in an industry have been declining since the 1990s. Arora et al. (2015) investigate the decline of innovation in leading firms and find out that such decline is mainly attributed to globalization, especially trade with China (the so-called "China trade shock"), and narrowing firms' scope.

Aghion et al. (2018) explore the effect of increasing export opportunities for French firms and the consequent changing innovation levels. Theoretically, two channels coexist, which would affect the innovations: 1. An expanding market would encourage all firms in the industry to innovate and develop new products 2. As the market expands and more firms enter, competition increases, profits decline, and thus discourage those low-productivity firms from innovating. Their empirical results demonstrate that while the high-productivity firms benefit from the export channel, the low-productivity firms are negatively affected in terms of innovations.

Later, Aghion et al. (2021) adopt the idea of input-output linkage and investigate the impact of "China Trade Shock" on French firms' outcomes, including employment and patent production. The study constructs both a horizontal trade shock and a vertical trade shock. More specifically, the vertical trade shock considers the weights of the inputs supplied into the industry, which sums over the direct import exposure experienced by all the industries as shares of the total inputs. The results have many interpretations- only horizontal trade shocks are shown to negatively and significantly affect firms' outcomes, while vertical trade shocks have no significant effects on those variables. However, the vertical shock has induced some firms to move away from manufacturing tasks to other service sectors with access to cheaper inputs in those sectors. For those manufacturing firms that stay in business, they are much more unlikely to develop new products. The horizontal shocks induced French firms to develop new products, which France has a more substantial comparative advantage. Lastly, cheaper imports from China allow some firms to remain profitable in areas where France has a weak comparative advantage. In general, their founding is primarily consistent with former literature by Autor et al. (2020) and Pierce and Schott (2016).

# *2. Background*

## *2.1. Theory of international trade*

As the famous economist David Ricardo praises, international trade would improve general welfare in the world. The standard textbook economics believes one of the most significant advantages of globalization is the liberation of trade, including goods, services, and culture. It is believed that bilateral trade may harm workers in industries with less comparative advantage. However, it stimulates the reallocation of resources to industries with more comparative advantages. Hence, even if a nation experiences short-term losses in some industries, it will, theoretically, be eventually better off as a whole since the gains from competitive industries would offset the losses. Economists advocate for free trade because they believe the nature of bilateral trade is Pareto-efficient. We have seen, in recent years, the pursuit of international trade agreements, such as the well-known North American Free Trade Agreement (NAFTA). There are also institutions, like the world trade organization (WTO), founded after the World War Two that aims to build a mature and efficient global market for trading.

## *2.2 The surge of Chinese exports*

In 1989, the Wall Street Journal predicted that China's economic growth would continue to stagger. In 2022, we observe the exact opposite case. After the economic reform took place, China embraced the global market fully. Export has grown significantly and China has become the so-called “Global Factory”. This phenomenon is highlighted by the growing share of world manufacturing exports, as shown in figure 1, which rises from 2.3% in 1991 to 18.8% in 2013.

[Please insert Figure 1 here]

This astonishing growth is made possible through two major factors: a successful transition from a central planning economy to a more market-based one and reducing trade costs after gaining access to the WTO. The reform in the 1980s and 1990s coordinates privatization and attracts more foreign direct investments. Hence, it greatly increases productivity and stimulates exports. After 2001, the year when China entered the WTO officially, China’s export growth surged, as shown in figure 2. In particular, the Chinese manufacturing sector benefits from greater access to imported inputs, hence boosting their productivity. Today, China has a large positive net export of manufacturing goods and a negative net export of raw materials.

### *2.3. Trade with the United States*

Since the economic reform, China’s export has started to rise steadily. By looking at the import penetration ratio for U.S. imports from China, we could see how imports from China have risen significantly, especially after joining the WTO in 2001. The import penetration ratio reached nearly 0.5 in 2007, suggesting that for each dollar spent, half is for Chinese imports.

As shown in Autor et al. (2016), China's share in U.S. manufacturing imports climbed up to 23.1% in 2011 from a modest 4.5% in 1991. This further demonstrates the weight of China's manufacturing imports in U.S.'s economy.

[Please insert Figure 2 here]

Moreover, the United States has been the origin of many modern technologies and is widely accepted as the center for innovation, emphasizing research & development, and investing funds for projects. Therefore, as shown in existing literature and figure 3, when the United States faces a decline in innovation levels (number of patents) after trading with China, it is crucial for policymakers to consider the general benefits of trade. From figure 3, we observe a sharp decline in the number of patents after 2001, when China joins the WTO. In Existing literature, Aghion et al. (2002) show that the relationship between competition and innovation is an inverted U-shape, as shown in the figure. On the other hand, another study by Bloom et al. (2016) suggests an increase in the absolute number of patents in European firms that are most affected by Chinese import competition. Hence, we wonder if there is a similar effect in U.S firms as well. In the following sections, we construct an overall picture and try to find empirical evidence to analyze this argument.

[Please insert Figure 3 here]

# *3. Research Design*

## *3.1 Data*

Our data of patents is a combination of the Compustat data with utility patents from the US patent and inventor Database, which is obtained from Autor et al. (2020) study. This database contains all patents granted by the trademark office between 1975 and 2013.

We obtain the firm-level data, such as sales, profitability, R&D investments and employment, for two subsequent periods (1991-1999, 1999-2007) from Autor et al. (2020). In terms of increasing competitive pressure from imports, we matched the industry-level trade exposure to Compustat that contains industry affiliation and financial statements on companies whose shares are traded at a North American stock exchange.

Adopting the supply-chain perspective, we applied data from the Input/Output (IO)-table provided by the US census bureau to match those upstream/downstream industries for a given industry. In addition, we specifically match the individual firm to one of the IO industries in the IO table. The IO-table measures the interdependences of industries in an economy, and it describes the sale and purchase relationships between industries.

### *3.2 Measurement*

Our main independent variable is the Chinese import penetration ratio/ trade exposure. After matching trade data to the 4-digit standard industrial classification (SIC) US manufacturing industries using the UN Comtrade Database and the crosswalk in Pierce and Schott (2012), Autor et al. (2013) create the baseline measure of trade exposure. We adopted the same definition: direct trade exposure is the change in the import penetration ratio for a US manufacturing industry over the period 1991 to 2007.

$$\Delta Direct_{j\tau} = \frac{\Delta M_{j,\tau}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}}$$

Where for US industry $j$, $\Delta M_{j,\tau}^{UC}$ is the change in imports from China over two subperiods, 1991 to 1999 and 1999 to 2007, and $Y_{j,91} + M_{j,91} - E_{j,91}$ is initial absorption. (Industry shipments, $Y_{j,91}$, plus industry imports, $E_{j,91}$, minus industry exports, $E_{j,91}$) at the start of the period. Moreover, following Autor et al. (2020), we select 1991 as the starting year for the analysis as it is the earliest period for which we have disaggregated bilateral trade data to match to US manufacturing industries.

Moreover, we adopted an instrumental variable to capture the simultaneous domestic shocks to US industries which influence both US import demand and innovation levels. Specifically speaking, China's export growth may be partly contributed to US industry import demand shocks, even if the major contributor is China's internal supply shock. In other words, the trade with China is bilateral which contaminates changes in import penetration. Hence, following the work of Autor et al. (2020), we instrument for initial trade exposure with the variable:

$$\Delta Direct_{j,\tau}^{IV} = \frac{\Delta M_{j,\tau}^{OC}}{Y_{j,88} + M_{j,88} - E_{j,88}}$$

Where $\Delta M_{j,\tau}^{UC}$ is the growth in imports from China industry $j$ during the period $\tau$ for a group of eight industrialized countries that does not include the United States. The initial absorption used is from 1988. Using this instrumental variable provides an advantage which is that industrialized and high-income economies are similarly exposed to China shocks, which induce similar effects such as falling sales. Moreover, another assumption made is that industry's internal demand shocks for China imports are uncorrelated.

We have calculated both the upstream and downstream shocks experienced by each industry and thus link them to firms, based on the IO-tables. The upstream shock is constructed using the industry's inputs to measure its exposure to the China shock. Since an industry may use several inputs from other industries, it is suspected that when other industries are exposed to Chinese competition, then the specific industry may be affected to some extent as well. We compute the upstream shock exposure as a weighted average of all of its inputs g's exposure to growth in China-sourced inputs [1]:

[1] To illustrate this calculation, suppose industry A uses inputs from 2 firms: industry B and industry C. if industry B and industry C face competition from China, then their price would change and it would affect firm A. Suppose firm A uses 40% inputs from industry B and 60% from industry C, then the upstream exposure is computed by: 0.4*China shock face by industry B + 0.6*China shock face by industry C

$$\Delta Up_{j,\tau} = 100 * \sum_{g} w_{g,j,1991}^{up} * \frac{\Delta M_{g,\tau}^{UC}}{Y_{g,91} + M_{g,91} - E_{g,91}}$$

where the denominator is the total absorption of inputs by US industry *g* in 1991, whereas the numerator is the change of US imports from China from 1991 to 2007 in industry *g*.

$$w_{g,j,1991}^{Up} = \frac{Z_{g,j,1991}^{UC}}{\sum_i Z_{i,j,1991}^{UC}}$$

The numerator in the weight represents imports of  input in sector *g* from China by US sector *j* in 1991, whereas the denominator is all intermediate inputs from China used by US industries *j*.

Similarly, the downstream channel is computed as the following:

$$\Delta Down_{j,\tau} = 100 * \sum_{k} w_{j,k,1991}^{down} * \frac{\Delta M_{k,\tau}^{UC}}{Y_{k,91} + M_{k,91} - E_{k,91}}$$

where the denominator is the total absorption of inputs by US industry *k* in 1991, whereas the numerator is the change of US imports from China from 1991 to 2007 in industry *k*.

The idea is to compute the annualized change in the sales-weighted average of the direct competition exposure of all of its customers. In contrast to the upstream channel, we look at the output industries of a given industry. Since an industry may sell to various downstream industries, we suspect that when these downstream industries are affected by the China shock, the given industry would be affected as well.

$$w_{j,k,1991}^{down} = \frac{Z_{k,j,1991}^{UC}}{\sum_i Z_{k,i,1991}^{UC}}$$

In the downstream channel, $Z_{g,j,1991}^{UC}$ indicates the US sector $j$'s output sales to US industry $k$ and the denominator represents the total sales of US industry $j$.

To capture the US domestic demand shock in the trade, we have also constructed alternative instrumental variables, using the same logic from the direct competition channel.

$$\Delta Up_{j,\tau}^{IV} = 100 * \sum_g w_{g,j,1991}^{up} * \frac{\Delta M_{g,\tau}^{OC}}{Y_{g,91} + M_{g,91} - E_{g,91}}$$

$$\Delta Down_{j,\tau}^{IV} = 100 * \sum_k w_{j,k,1991}^{down} * \frac{\Delta M_{k,\tau}^{OC}}{Y_{k,91} + M_{k,91} - E_{k,91}}$$

### *3.3 Specification*

We aim to explore the causal effects of increasing import exposure on various outcomes of interests. Our baseline regression is:

$$\Delta Patent_{ij\tau} = \alpha + \beta_1 \Delta Direct_{j\tau} + \beta_2 \Delta Up_{j,\tau} + \beta_3 \Delta Down_{j,\tau} + Z_{i\tau} + \varepsilon_{i\tau}$$

We use data from 1991 to 2007, following the work of Autor et al. (2018), to estimate this regression model. Our main dependent variable is the relative change in patent, which is defined as the first difference in patents over a period $t$, $t + 1$, divided by the average number of patents across the two periods $t$ and $t + 1$. $\Delta Patent_{ij\tau}$ is 100 times the annualized change in patent over the relevant time interval τ for a given firm $i$ belong to industry $j$. $\Delta \mathrm{Direct}_{\mathrm{j},\tau}$ , $\Delta \mathrm{Up}_{\mathrm{j},\tau}$ and $\Delta \mathrm{Down}_{\mathrm{j},\tau}$ are 100 times the annualized change over the period τ (1991 to 2007) in direct, upstream and downstream exposures to trading with China ,respectively. $\mathrm{Z}_{i\tau}$ is a set of start-of-period control variables.

[Please insert Table 1 here]

Since our main target is to establish a significant positive impact from the upstream channel, we compute the top five industries that are most affected by upstream exposure and five industries that are least affected.

[Please insert Table 2 here]

Later, we run variants of the baseline regression using instrumental variables and different dependent variable. We adopt a 2-Stage-Least squares (2SLS) model and instrument each exposure channel. To address the problem of the possible endogenous nature of US imports from China, we use three instrument variables (IV). We suspect that there could be a simultaneity issue in the bilateral trade with China, as potential US demand shocks may induce increasing imports as well. Thus, we consider other 8 high-income countries, assuming that they have been affected by China supply/export shocks similarly. Another important assumption is that these demand shocks are uncorrelated across high-income countries.

## *4. Estimation Results*

### *4.1 Innovative outcomes accounting for upstream "China Trade Shock"*

We now use the regression model to examine the effect of Chinese imports on US domestic patent production. Column (1) is a barebone specification, following the work of Autor et al. (2020), which regresses patent production on direct import exposure only along with other controls, using an instrumental variable. The point estimate is significantly negative at the 1% level, indicating that direct exposure reduces US innovative abilities by 11%. Column (2) adopts a 2SLS approach, confirming the effect and the point estimate shows a greater negative effect, which reduces the relative change in patents by 14%. Column (3) adds the upstream exposure to the specification and uses the OLS approach. Similarly, direct exposure is shown to be negatively affecting significantly. The point estimate of upstream exposure is significantly positive, which supports our hypothesis. Column (4) adopts a 2SLS approach, showing similar results to column (3) as well, where the point estimate demonstrates a greater negative effect from the direct channel as well as a slightly greater positive effect from the upstream channel. For all specifications, both the direct and upstream exposure has a significant impact on US innovation outcomes.

[Please insert Table 3 here]

### *4.2 Innovative outcomes: robustness check*

We now add another variable- downstream exposure to the baseline regression model. Since the downstream channel would produce a reinforcing effect on the direct channel hypothetically, we include this for the purpose of a robustness check. Column (3) places downstream exposure and supports the results from column (2), which suggest a smaller impact of direct exposure and a greater impact of upstream exposure. However, the downstream exposure has a positive impact on patent production, although insignificantly. Column (4) adopts a 2SLS approach, showing similar results to column (3) as well. The point estimate displays a greater negative effect from a direct channel and a smaller positive effect from an upstream channel. Again, the downstream channel generates an insignificant result.

[Please insert Table 4 here]

### *4.3 Split-sample analysis: which firm is affected the most?*

We have split our sample into two halves, based on their performance in their own industries- whether the supposed indicator is smaller or greater than the industry's average, according to four metrics: sales per worker, capital per worker, profit over capital (ROI), and debt to equity. The odd-numbered columns estimate the effect of import competition on patenting for firms that outperform their respective industry's mean in terms of higher productivity, capital intensity, profitability, and lower indebtedness. The even-numbered columns present analogous regressions for the complementary samples.

We examine how the two groups' patent production differs. In terms of labor productivity, as shown in column (1), firms that are more productive confront greater innovative pressure from the direct channel. However, firms that have less capital intensity, lower profitability and higher debt experience a fall in innovation more significantly than their counterpart, when confronting direct exposure. In the upstream channel, we find out that firms which have lower labor productivity experienced greater loss of innovation. On the other hand, contrasted with the direct channel, firms that have lower capital intensity, lower ROI and higher debt experience a greater positive impact on patents. For the downstream channel, we observe a similar pattern with the direct channel, despite insignificantly and smaller point estimates. Our results confirm that firms that are in less competitive positions initially will encounter more furious innovative pressure from direct competition. This effect is statistically significant for the sample split by profitability and debt-equity ratio.

What's worth noting is, we could see offsetting effects in column (4), (6) and (7), where the upstream exposure generates a positive effect that is large enough to offset the negative effect by direct channel. On the other hand, we observe some dominating effects in the direct channel, such as in column (1), (5) and (8). The direct exposure produces a larger negative impact on patent production than the upstream channel's positive impact.

[Please insert Table 5 here]

## *5.Discussion*

Our estimation's results are consistent with existing literature in certain ways. Firstly, the direct exposure would induce a decline in US firms' innovations, measured by relative change in patents production. Following Autor et al. (2021), we also found that firms that are less competitive initially in their own industries would be worse off in terms of patent production when facing direct China shock.

However, we also discovered a significant positive impact in the upstream channel that successfully offset most of the negative impact indued from the direct channel. Our estimates show that when a specific firm's upstream firms are confronted with China shock, the innovation level in this specific firm would be enhanced. This provide more solid evidence on the beneficial side of trade, which is missing from the existing literature. Aghion (2018) examine the upstream channel in France but does not find a significant positive impact. Moreover, in the split-sample analysis, there are similar offsetting results in some indicators.

## *6. Conclusion*

In conclusion, our paper posits an argument that contrasts with the mainstream literature, notably Autor et al. (2020). We confirm some of their results, but overturn the main conclusion of theirs. After introducing the upstream channel, we discover a significant positive impact to patent production that is large enough to offset most of the direct channel's negative effect. We may arrive at the conclusion that Chinese import competition creates two effects to US domestic innovation levels, which at the end approximately counterbalance with each other. Hence, it may be premature to say that Chinese imports have reduced US innovation levels afterall.

Nevertheless, this paper does not discover a significant downstream exposure's effect on strengthening the direct channel's impact. Therefore, we remain open-minded to additional research of this topic.

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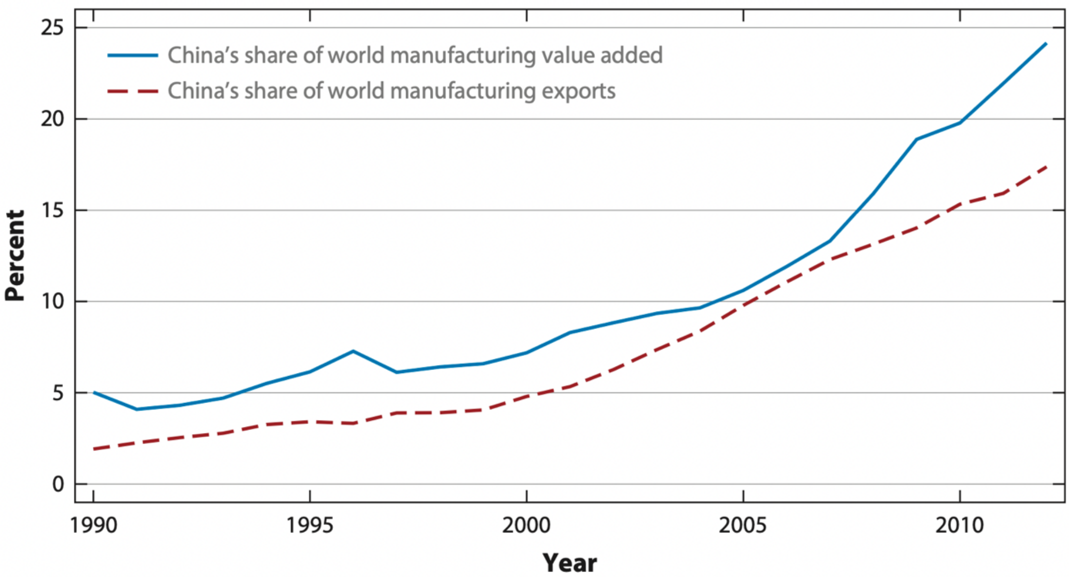
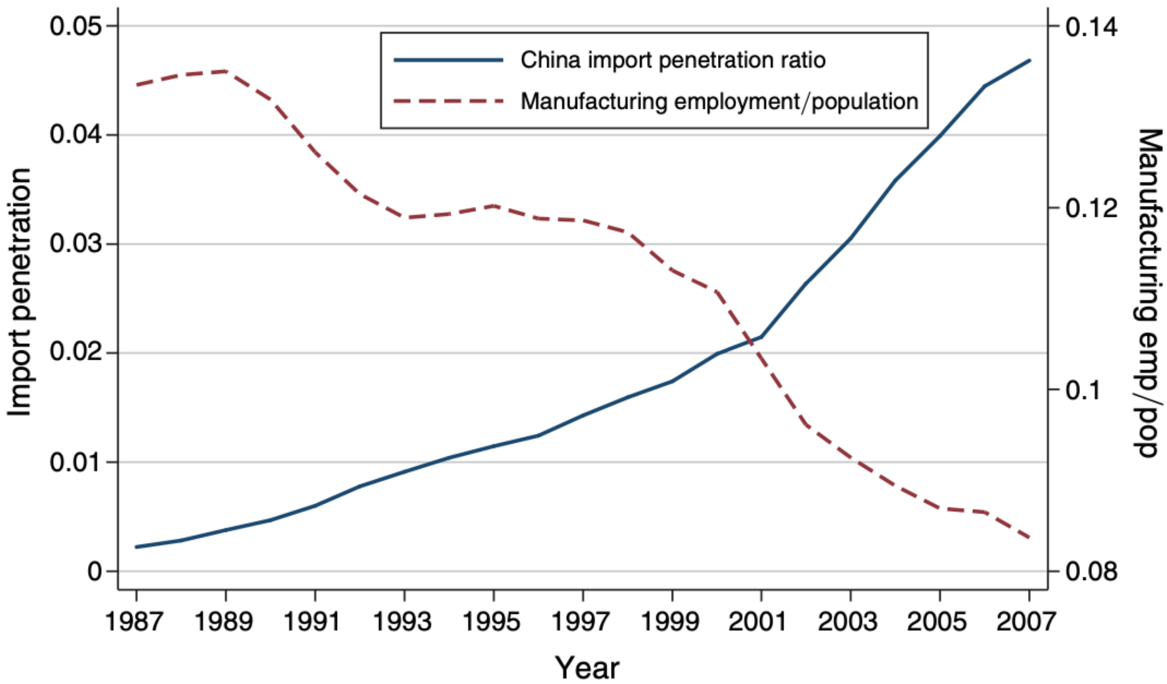
## *8. Figures*

Figure 1- China's share of world manufacturing activity (1990-2012)



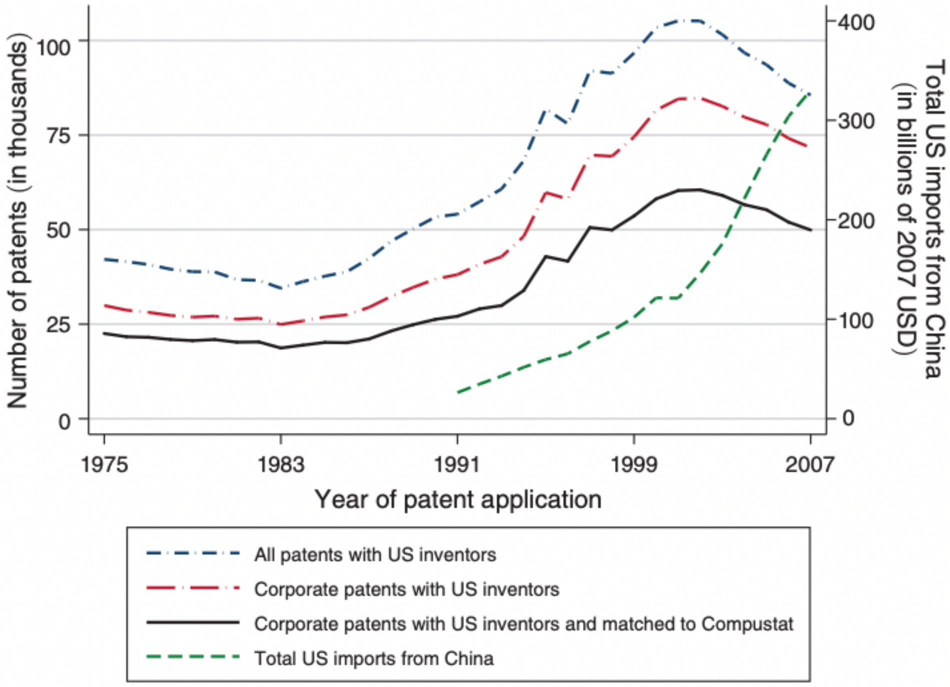

*Notes*: This figure is extracted from *The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade* by *David H. Autor, David Dorn, and Gordon H. Hanson*. Data source is from World Development Indicators.

Figure 2- Ratio of Chinese imports to U.S. Domestic consumption




*Notes*: This figure is extracted from *The China Syndrome: Local Labor Market Effects of Import Competition in the US* by *David H. Autor, David Dorn, and Gordon H. Hanson.*

Figure 3- Number of patents by application year




*Notes*: This table is extracted from Foreign Competition and Domestic Innovation: Evidence from US Patents by David Autor, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu

# 9. Tables

Table 1--Summary Statistics of dependent variables and independent variables

| | *Observations* | *Mean* | *Std* | *$10^{th}$ percentile* | *Median* | *90th percentile* |
|---|---|---|---|---|---|---|
| Main Dependent Variables | | | | | | |
| *Patents* | 5,725 | 0.009 | 1.00 | -1.185 | 0.000 | 1.185 |
| Independent Variables | | | | | | |
| *Direct Exposure* | 5,725 | 0.510 | 1.00 | 0.018 | 0.149 | 1.424 |
| *Upstream Exposure* | 5,725 | 1.568 | 1.00 | 0.614 | 1.241 | 3.087 |
| *Downstream Exposure* | 5,725 | 0.494 | 1.00 | 0.008 | 0.079 | 1.592 |

*Notes*: all variables have been standardized.

Table 2 --Top 5 and Bottom 5 Industries' upstream exposure

| SIC Industries | Upstream exposure |
|---|---|
| *Highest 5* | |
| Mobile homes | 4.95 |
| Printing Trade Machinery | 5.19 |
| Operative Builders | 7.58 |
| Nonresidential Building Construction | 7.58 |
| Subdividers and developers | 7.99 |
| *Lowest 5* | |
| Knitting Outwear Mills | .107 |
| Fats and Oils | .109 |
| Natural Gas Distribution | .111 |
| Meat Packing Plants | .127 |
| Distilled and blended liquors | .129 |

*Notes*: this table displays the 5 industries that are affected by Chinese import competition the most and least from the upstream channel. The upstream exposure has been standardized (standard deviation=1), hence the coefficient reflects an economic value directly.

Table 3 – Impact of Chinese import competition on firm-level patenting from two channels, 1991-2007: OLS and Instrumental Variables Models. Dependent Variable: change in patents by US-based investors relative to mid-period number of patents.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | $\Delta Patent$ | $\Delta Patent$ | $\Delta Patent$ | $\Delta Patent$ |
| | OLS | 2SLS | OLS | 2SLS |
| Direct Exposure | -11.426*** | -14.413** | -12.160*** | -14.785** |
| | (3.911) | (7.067) | (4.178) | (7.008) |
| Upstream Exposure | | | 13.220** | 13.536** |
| | | | (6.190) | (6.371) |
| Manufacturing Controls | Yes | Yes | Yes | Yes |
| Firm Controls | Yes | Yes | Yes | Yes |
| Technology Mix | Yes | Yes | Yes | Yes |
| 2 lags | Yes | Yes | Yes | Yes |
| Year Control | Yes | Yes | Yes | Yes |
| Observations (N) | 5725 | 5725 | 5725 | 5725 |
| R-sq | 0.227 | 0.233 | 0.227 | 0.233 |

*Notes*: Each column represents a firm-level regression of the dependent variables. This table takes the direct and upstream exposure as independent variables. The dependent variable-relative change in patents- is the difference in patents over a period t, t + 1, divided by the average number of patents across the two periods t and t + 1. Column (1) and (2) uses OLS approach, while Column (3) and (4) uses 2SLS approach, instrumenting the direct and upstream exposure. All regression models adopt the same controls. Manufacturing controls are a set of dummies for 5 manufacturing sectors. Firm controls include R&D-to-sales ratio and two dummies indicating firms for which the value of log U.S sales and R&D-to-sales ratio are not available in the data. The Technology Mix controls for the fraction of a firm's patents by broad technology category, which includes six major patent technology categories. The 2 lags represent the control for two 8-years lag of relative change in patents. The last control is a variable indicating the period/year, which is either 1991 or 1999. The regression models are all weighted based on the firm's patents averaged over the start and end of a period, following Autor (2020). And all standard errors are clustered on four-digit SIC industries. This table has standardized the independent variables (standard deviation = 1), so the coefficients represent an economic value directly. Robust standard errors are shown in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1%

Table 4- Impact of Chinese import competition on firm-level patenting from three channels, 1991-2007: OLS and Instrumental Variables Models. Dependent Variable: change in patents by US-based investors relative to mid-period number of patents.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | $\Delta Patent$ | $\Delta Patent$ | $\Delta Patent$ | $\Delta Patent$ |
| | 2SLS | 2SLS | OLS | 2SLS |
| *Direct Exposure* | -14.413** | -14.785** | -12.351*** | -15.618** |
| | (7.067) | (7.008) | (3.809) | (6.170) |
| *Upstream Exposure* | | 13.536** | 14.745** | 13.665** |
| | | (6.371) | (5.795) | (6.437) |
| *Downstream Exposure* | | | 5.556 | 3.138 |
| | | | (3.789) | (4.885) |
| *Manufacturing Controls* | Yes | Yes | Yes | Yes |
| *Firm Controls* | Yes | Yes | Yes | Yes |
| *Technology Mix* | Yes | Yes | Yes | Yes |
| *2 Lags* | Yes | Yes | Yes | Yes |
| *Year Control* | Yes | Yes | Yes | Yes |
| *Observations (N)* | 5,725 | 5,725 | 5,725 | 5,725 |
| *R-sq* | 0.227 | 0.233 | 0.234 | 0.234 |

*Notes*: Each column represents a firm-level regression of the dependent variables. This table takes the direct, upstream exposure and downstream exposure as independent variables. The dependent variable- relative change in patents- is the difference in patents over a period t, t + 1, divided by the average number of patents across the two periods t and t + 1. Column (1) and (2) uses 2SLS approach. Column (3) uses OLS regression model and (4) uses a 2SLS approach, instrumenting the direct, upstream and downstream exposure. All regression models adopt the same controls. The controls are defined the same as in table 3. All standard errors are clustered on four-digit SIC industries. This table has standardized the independent variables (standard deviation = 1), so the coefficients represent an economic value directly. Robust standard errors are shown in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1%

Table 5- Split-sample Analysis Effect of Chinese Import Competition on Patenting 1991–2007: Sample Splits by Initial Firm Sales/Worker, Capital/Worker, ROI, and Debt/Equity. Dependent Variable: Relative Change in Patents

| | *Firm labor productivity and capital intensity* | | | | *Firm profitability and leverage* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Sales/worker* | | *Capital/worker* | | *Profit/capital (ROI)* | | *Debt/equity* | |
| | *>Avg* | *< Avg* | *> Avg* | *< Avg* | *>Avg* | *< Avg* | *> Avg* | *< Avg* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Direct Exposure* | -27.304*** | -11.075 | -14.056 | -26.103*** | -18.150*** | -27.147*** | -31.248** | -21.222*** |
| | (9.813) | (10.373) | (14.987) | (6.270) | (6.773) | (5.801) | (14.287) | (8.103) |
| *Upstream Exposure* | 3.864 | -6.235 | -9.970 | 24.313* | -3.422 | 28.226 | 31.237 | 0.374 |
| | (16.793) | (15.196) | (17.505) | (14.633) | (14.784) | (17.435) | (22.603) | (13.848) |
| *Downstream Exposure* | 7.459 | -19.944 | -0.674 | -0.938 | 6.753 | -17.334* | -25.276* | 15.559 |
| | (10.912) | (13.593) | (12.750) | (11.887) | (8.775) | (9.927) | (14.024) | (10.851) |
| *Full Controls* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations (N)* | 1,018 | 1,836 | 1,121 | 1,735 | 1,367 | 1,670 | 520 | 2,207 |

*Notes*: each column is a representation of 2SLS regression model, comprising two stacked differences, 1991-1999 and 1999-2007. All models include the full set of controls in table 3 and 4. Columns 1–2, 3–4, 5–6, and 7–8 split the firm sample into firms whose sales per employee, capital per employee, ROI, or debt-to-equity ratio is above/below the patent-weighted industry average in the start-of-period year. All models are weighted by a firm's US-inventor patents averaged over the start and end of a period. Standard errors are clustered on four-digit SIC industries. This table has standardized the independent variables (standard deviation = 1), so the coefficients represent an economic value directly. Robust standard errors are shown in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5%, and 1%.

## *Acknowledgment*

Born in a family that makes a living from operating a small factory in the manufacturing sector, I often hear my dad complaining about how the trade war between China and the United States has affected the sales of the factory, causing severe losses. After I entered high school and encountered economics, I read more books, which include the famous economist Joseph Stiglitz's "Making Globalization Work." This intelligent book provided me with some valuable insights into some unintentional downsides of global trade, which helped me to become increasingly interested in this topic. On the other hand, I read more news from some mainstream U.S. reporters, mostly about the negatives of trading with China, such as declining employment. Dr.Sun coincidentally shares an article with me about innovation levels in the U.S. and how they are affected by China's imports. I began to think whether I could find some results that prove that this bilateral trade is not causing harm to the U.S. as they have claimed. I then shared my thoughts with Dr.Sun and sought assistance from him. He generously resolved many of my queries and pointed out some possible research directions. I am most grateful for all the help he has given to me.