**Preliminary**

# U.S. county-level impacts of growth in China's demand for agricultural imports[a]

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**Abstract:** We use county-level data on agricultural outcomes and data on China's imports of field crops to study the effect of growth in U.S. agricultural exports to China on U.S. county-level outcomes. A well-known instrumental variables strategy is used to isolate the Chinese import demand shock from other determinants of bilateral trade growth. Our first stage regressions indicate that China's import demand growth explains most of the cross-county variation in growing exposure to China. Our second stage results offer mixed evidence that the import demand shock affected the agricultural outcomes we study. We attribute increases in total cropland acres to Chinese import demand growth, as well as decreases in two measures of government payments. While the estimated effects are large economically, the statistical evidence of China's influence is generally weaker than other authors observe for manufacturing. It is likely that the consequences of the China shock on agriculture were subsumed by other shocks that occurred during this period.

Keywords: Agricultural trade with China, Responses to trade shocks, Trade in field crops

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## Section 1. Introduction

The entry of China into international markets has been an important event producing winners and losers across the globe. Prominent recent work by Autor, Dorn and Hanson (2013) demonstrates that the export supply shock associated with China's entry into world markets for manufactured goods substantially disrupted local U.S. labor markets that were exposed to import competition from China. A number of related papers link other U.S. outcomes to the China shock in manufacturing, including degraded local public finances (Feler and Senses, 2016), decreased earnings and increased use of public disability benefits (Autor et al 2014.), and increased innovation in manufacturing (Zhang 2017). The method has also been used to link increased Chinese exports to employment outcomes in Japan (Yamashita 2017) and to political support for far-right parties in Germany (Dippel et al. 2017).

This literature has focused attention on the consequences of increased import competition from Chinese manufactured goods. Another consequence of Chinese entry into global markets has been a large positive demand shock for U.S. food and agricultural products. In 1992, China accounted for just 1.16 percent of U.S. agricultural exports, while China's share had grown to 13.74 percent by 2017 (USDA, 2018). Export growth occurred not only in market share, but also in absolute levels. The large and growing role that China plays as an export destination for U.S. agricultural products leads us to ask: are the effects of Chinese agricultural outputs visible down on the farm?

In this paper we adapt the instrumental variables (IV) strategy of Autor, Dorn and Hanson (2013) to study the consequences of Chinese demand shock on agricultural outcomes in U.S. counties. We use changes in Chinese imports of field crops from ten other large agricultural exporters to construct an instrument for U.S. counties' increased exposure to Chinese imports of field crops. This approach isolates the Chinese import demand shock from any U.S. export supply shock that may be influencing U.S. China trade. In the second stage, we investigate the effects of increased Chinese demand for U.S. field crops on six outcome variables measured at the county-level: total cropland acres, the value of crops, the estimated market value of agricultural land and buildings, total acres harvested, total government payments received, and average government payments per farm.

In our preferred sample, which defines the Chinese demand shock over the years 1997-2012, we find that counties that were more exposed to China's import demand shock saw economically and statistically significant increases in the total acres in cropland. We also estimate a negative effect of growing Chinese demand on two measures of government payments. The estimate effects on other outcome variables are weaker, statistically, and the sign of the treatment effect varies over the sample in our (preferred) non-linear model.

In general, our results suggest sizable effects of the China shock, but levels of statistical confidence are much lower than those that ADH report for manufacturing employment outcomes. It is likely that there are two main reasons for this: 1) the China shock in agriculture was swamped by other shocks in agriculture (e.g. changing US farm policy, other ag trade shocks, and more), and 2) crop-switching possibilities in agriculture mean that the effects of demand shocks linked to specific crops have more muted effects on land than demand shocks on manufacturing industries have on labor (with industry specific-skills).

The outline of the paper is as follows: Section 2 provides background on U.S. China trade in agricultural products, and reviews the literature. Section 3 outlines the methodology. Section 4 describes the data. Section 5 provides results. Section 6 concludes.

## Section 2. Background and Literature review

### Section 2.1 Background of U.S. China Agricultural Trade.

China began its economic "Reform and Opening Up" in 1978.[1] The country's agricultural trade also began to increase at the same time. Total agricultural sector trade has increased by more than an order of magnitude, from 6.1 billion dollars in 1978 to 78.1 billion dollars in 2007. China has gone from near autarky in agricultural products to become one of the World's largest agricultural traders during these 40 years. However, instead of steady development of global agricultural trade, U.S. and China's agricultural trade progress has been separated into 2 different time periods: pre-1990 and post-1990 (Niu, 2009).

In the pre-1990s period, under the background of a planned economy, agricultural imports into China were determined by the difference between planned production (set by the government) and the actual demand. However, transitions were also happening at the same time. China's trade partners gradually started to shift, from a set of countries that were mainly Socialist

[1] "Reform and Opening Up" refers to the program of economic reform termed "Socialism with Chinese characteristics" in the People's Republic of China that was started in Dec, 1978. It has resulted in immense changes in Chinese society with greatly decreased poverty and high-speed economic growth.

to a much larger set of countries all over the world. Growth of trade with the U.S. was part of this transition.

In the 1990s, China began negotiations to enter the global market. The U.S. was an important negotiating partner in this process. In 1992, the U.S. and China reached a memorandum of understanding on market access, under which the U.S. undertook to “firmly support China in its effort to obtain its status as a Contracting Party to GATT”. In 1994, China signed the Final Act Embodying the results of the Uruguay Round of Multilateral Trade Negotiations and the Agreement Establishing the Multilateral Trade Organization, thus taking one step nearer to regaining its GATT Contracting Party Status (Wang, 1994). This was China’s global trade position as it stood on the threshold of entry to the WTO in 2001.

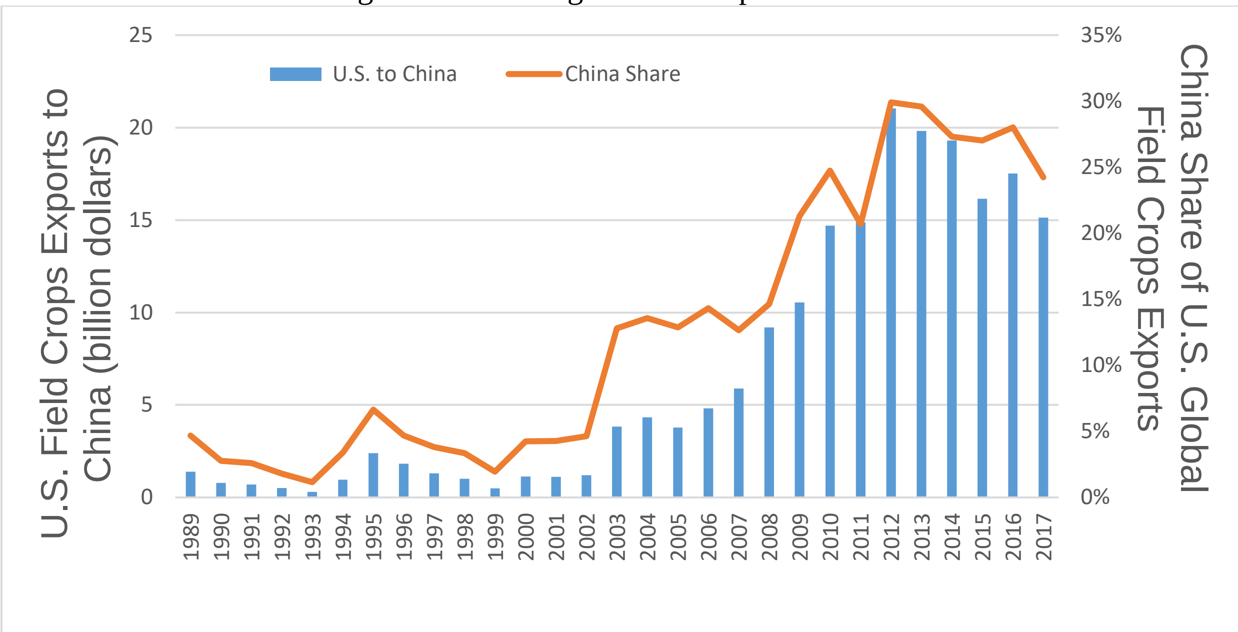
China also adjusted its own agricultural policy to become compliant with international trade rules. From 1992 to 1997, China decreased its agricultural trade tariff level in four consecutive years. Also, China began to use the Harmonized System, a global system of names and numbers to classify traded products.[2] Compounding the positive effects of internal reforms on China’s trade is the country’s accession to the WTO, which gave it most-favored nation status among the WTO members (Branstetter and Lardy, 2006). With all these negotiations and changes during the 1990s, U.S. and China’s agricultural trade began to grow with a steady pace; they are now one of each other’s largest agricultural trade partners.

Figure 1 shows the growth in U.S. agricultural exports to China, both in absolute and relative terms. Both the total value of U.S. exports to China and China’s share of U.S. exports are relatively flat before 2002, rising sharply up through 2012, and falling thereafter. Because we want to include the entry of China into the WTO in 2001, we will study the effects of Chinese trade growth over the 15-year period: 1997-2012.[3] In robustness checks we study the 2002-2012 period.

[2] As China only began to use HS codes in 1992, the trade data between China and other countries are not available before the year of 1992. See further in Data Chapter.

[3] Our U.S. county-level outcome data are taken from the U.S. Censuses of Agriculture. 1997 is the latest such census that predates China’s WTO entry.

Figure 1.1: U.S. Agricultural exports to China




Notes: U.S. Agricultural exports to China reported in billions of U.S. dollars (left hand scale) and China's share of global U.S. exports (right hand scale) Data from Economic Research Service analysis of data from USDA, Foreign Agricultural Service, Global Agricultural Trade System.

### 2.2 The China Syndrome – Paper of Autor, Dorn and Hanson

As China has become an important U.S. trading partner, questions have been raised about the effect of this trade on the U.S. Growing U.S. imports of manufacturing goods from China has put pressure on U.S. manufacturers of competing products. Declining U.S. manufacturing employment is plausibly linked to imports from China, but other factors such as technological innovation also matter. Thus, the real question is how much of this change is due to imports from China?

Autor, Dorn and Hanson answered this question in their paper "The China Syndrome". They analyzed the effect of rising Chinese import competition between 1990 and 2007 on U.S. local labor markets. The method they were using was to find out initial differences in industry specialization in order to exploit cross-market variation in import exposure. Additionally, they instrument for U.S. imports using changes in Chinese imports by other high-income countries to exclude U.S.-specific supply and productivity shocks. (Autor, Dorn and Hanson, 2013).

At first, they found that there exists a clear negative relationship between U.S. employment in manufacturing and China's import penetration ratio[4], as in higher Chinese imports would cause lower employment in manufacturing. To find out the local impact of Chinese imports, they localize the U.S. labor market using the concept of commuting zones (CZs)[5]. These commuting zones differ in their exposure to import competition as a result of regional variation in the importance of different manufacturing industries for local employment. Their main measure of this local labor market exposure to import competition is the change in Chinese import exposure per worker in a region, where imports are apportioned to the region according to its share of national industry employment:

$$\Delta IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}} \tag{2.1}$$

In this expression, $L_{it}$ is the beginning-of-period employment (year *t*) in region *i* and $\Delta M_{ucjt}$ is the observed change in U.S. imports from China in industry *j* between the start and the end of the period (Autor, Dorn and Hanson, 2013). Then they link this import exposure change across time periods with local labor market outcomes such as employment rates, wages, public transfer payments and household incomes for their estimations.

However, inside this methodology, the major empirical challenge in identifying the causal effect of Chinese imports is the unobservable U.S.-specific demand shocks. Realized U.S. imports from China in equation (2.1) may be correlated with industry import demand shocks, biasing OLS estimates of the effects of increased imports from China on U.S. manufacturing employment. The core assumption here is that China's internal supply shocks, as in its own economic development and falling trade costs, is the reason of the surge of Chinese imports instead of U.S.-specific demand and productivity shocks.

[4] The import penetration ratio was defined by U.S. imports from China divided by total U.S. expenditure on goods, measured as U.S. gross output plus U.S. imports minus U.S. exports.

[5] Logical geographic units for defining local labor markets that encompasses all metropolitan and nonmetropolitan areas in the U.S (Tolbert and Sizer, 1990).

To deal with this endogeneity issue Autor et al, used the instrumental variable strategy based on Chinese export growth into other high-income markets[6]. This strategy would identify the Chinese productivity and trade-shock component of U.S. import growth if the common with-in industry component of rising Chinese imports to the U.S. and other high-income countries stems from China's comparative advantage and fall in trade costs, thus ruling out the U.S.-specific demand and productivity shock component. These other high-income countries also endured with the surge of Chinese imports, while at the same time, were not correlated with U.S. local markets outcomes, which makes it a good instrument choice.

Similarly, the instrumented variable was expressed the same way. They use other 10 high-income markets' imports from China instead of U.S. imports from China. Also, the use of lagged employment levels mitigates the possibility that employment is contemporaneously adjusting to anticipated Chinese trade and the use of other high-income countries:

$$\Delta IPW_{oit} = \sum_j \frac{L_{ijt-1}}{L_{ujt-1}} \frac{\Delta M_{ocjt}}{L_{it-1}}$$

With this instrumental variable strategy, one would be able to show that China's rising productivity and falling trade costs is the cause of U.S. import growth. And most importantly, it allows one to estimate causal effect of local exposure to Chinese imports and U.S. local labor outcomes, such as employment rate, wage, public transfer payments and household incomes. In short conclusion, they found that rising Chinese imports in manufacturing industry causes higher unemployment, lower labor force participation and reduced wages in local labor markets that house import-competing manufacturing industries.

### 2.3 Adapting the strategy to study U.S. agricultural exports

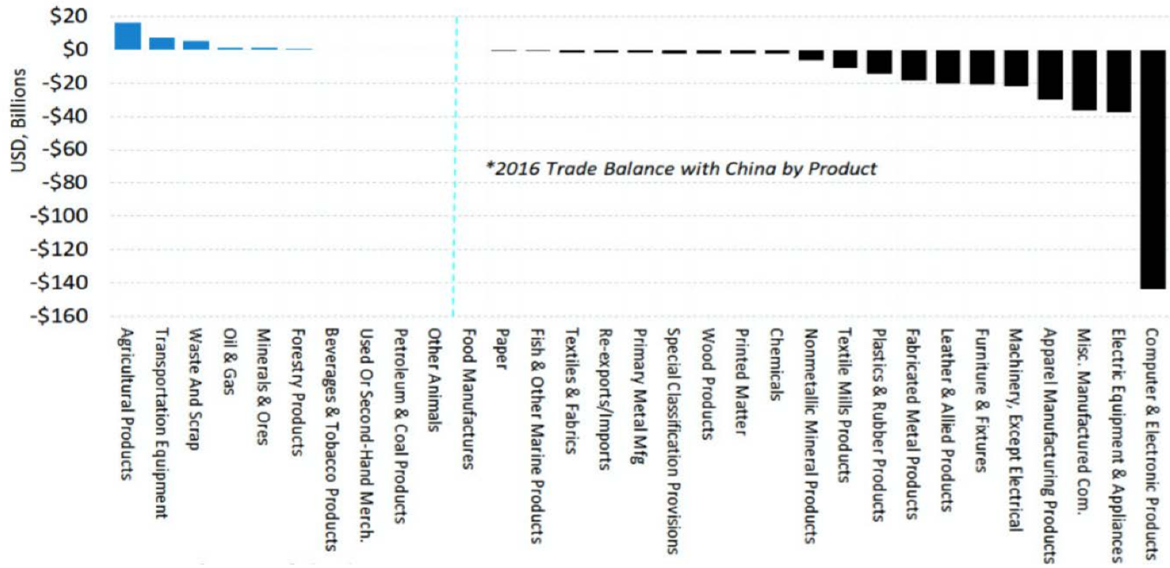
Thanks to the major contribution of Autor, Dorn and Hanson's work, a series of papers investigate the relationship between local Chinese import exposure and different types of local outcomes such as housing prices and business activity (Feler and Senses, 2016), cumulative earnings and public disability benefits (Autor, Dorn, Hanson and Song, 2014), U.S. manufacturing firms innovation level (Zhang, 2017), impact on voters (Dippel et al., 2017) and

[6] The other eight high-income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

other countries' employment level such as Japan (Yamashita, 2017). All these studies use the same or highly localized instrumental variables $\Delta IPW_{uit}$ and $\Delta IPW_{oit}$ from Autor, Dorn and Hanson, indicating that this is a very well-accepted research method.

All these studies estimate the effects of China's entry into markets for manufacturing goods. China's emerging dominance as a manufacturing exporter has led to different consequences across different areas. But during this time, China has become a major importer of agricultural products. Unlike manufacturing products, agricultural commodity is one of the few products that U.S. has a trade surplus with China (Figure 2.1). Also, U.S. has been leading in many agricultural commodities of China's imports (Table 2.1). Thus, the same techniques that Autor, Dorn and Hanson use to study the effects of Chinese manufacturing exports can be used to study the effect of Chinese agricultural imports.

Figure 2.1: U.S. Trade Balance with China, by sector, in 2016




Source: U.S. Department of Commerce

Table 2.1: U.S. Share of China's Leading Agricultural Imports, 2012-2013

| Item | Average Chinese import value<br>*$ Billion* | U.S. share of China's imports<br>*% Percent* | U.S. rank<br>*Number* |
|---|---|---|---|
| All agricultural products | 109.0 | 24 | 1 |
| Soybeans and other oilseeds | 40.6 | 36 | 1 |
| Fats and oils | 11.9 | 2 | 11 |
| Cotton | 10.1 | 30 | 1 |
| Meat | 5.0 | 25 | 1 |
| Cereal grains | 4.9 | 42 | 1 |
| Dairy | 4.2 | 10 | 2 |
| Fruit and nuts | 3.9 | 13 | 4 |
| Wine and beverages | 3.1 | 3 | 7 |
| Cattle hides | 2.6 | 53 | 1 |
| Wool | 2.7 | < 1 | 13 |
| Baking products | 2.3 | 4 | 13 |
| Vegetables | 2.5 | 2 | 5 |
| Sugar | 2.5 | 5 | 5 |
| Fish meal | 1.7 | 15 | 2 |
| Distillers' dried grains | 1.1 | 99 | 1 |
| Tobacco | 1.4 | 11 | 3 |
| Live animals | 0.5 | 15 | 3 |
| Hay and forage products | 0.2 | 95 | 1 |

Source: USDA, Economic Research Service Analysis of China's custom Statistics

## Section 3. Method

Our estimation strategy of deriving a causal relationship between local Chinese agricultural exports exposure and local agricultural outcomes is based on the empirical framework developed in Autor, Dorn and Hanson (2013). In this section, we introduce the strategy to calculate aggregated county level exposure to Chinese exports, discuss the endogeneity threat to this strategy in terms of trade shocks and implement the instrumental variable approach to counter the threat for our main specifications.

### Section 3.1 Export exposure to China

We use a measure of exposure over time to Chinese exports as the source of variation in local agricultural outcomes. County level data are available, and there is no natural aggregate like the commuting zones in Autor, Dorn and Hanson's paper. Our unit of analysis is therefore the county. Also, instead of using regional employment numbers, we construct acres harvested from each county for one commodity as a baseline input with different kinds of agricultural commodities in place of different manufacturing industries. Additionally, Autor, Dorn and Hanson were using manufacturing employment as their primary variable, while we study the estimated value of farmland and buildings, total acre harvested, government payments, total cropland acres and value of crops as they are reported in the census of Agriculture[7]. In contrast to Autor, Dorn and Hanson's imports per worker variable, we calculate export value per 100 acres, which we measure at the county level. The change in exports per 100 acres is constructed as the expression below:

$$\Delta EPA_{uit} = \sum_j \frac{A_{ijt}}{A_{ujt}} \frac{\Delta E_{ucjt}}{A_{it}/100} \qquad (3.1)$$

In this expression, $\Delta EPA_{uit}$ is the change in U.S. export exposure in year *t* county *i*. $\frac{A_{ijt}}{A_{ujt}}$ is the proportion of county *i*'s production of commodity *j* in the whole U.S. at the start of year *t*. $A_{it}$ is the beginning-of-period production (year *t*) in county *i* and $\Delta E_{ucjt}$ is the observed change in U.S. exports to China in commodity *j* between the start and the end of the period.

[7] Autor, Dorn and Hanson's trade variable is imports from China at SIC 4 digits level of aggregation. Our trade variable is U.S. exports of field crops to China, where we concord the trade data to production data on field crops, aggregating where necessary. See further at Section 4.

Basically, $\frac{A_{ijt}}{A_{ujt}}$ gives us a percentage of a specific commodity's national portion in year *t* county $j$. Then we multiply the export difference $\Delta E_{ucjt}$ (in dollars) with this percentage, attributing a proportion of the change in exports to county *j* in year *t*. At last, we divide this product by the value of the county's total field crop production and sum over the commodities to calculate each county's change in export exposure to China. The unit of $\Delta EPA_{uit}$ is dollars/ 100 acres. In general, this expression apportions the change in the value of U.S. exports to China in a specific commodity depending on how this commodity's acres harvested is initially distributed across counties in the U.S. and then rescales this value by county's total acres harvested.

**Section 3.2 Endogeneity of trade shocks**

A major empirical challenge in identifying the causal effect of exports to China and local outcomes across counties is the presence of unobserved U.S. specific positive supply and productivity shocks, implying, in other words, that changes in U.S. agricultural supply and productivity could be driving changes in U.S. exports per acre. The alternative I emphasize is that growth in U.S. exports to China was primarily due to structural reforms within China. To tackle this endogeneity issue, we follow Autor, Dorn and Hanson's instrumental variable strategy, to separate Chinese demand and U.S. supply shocks, we use data from 10 other largest agricultural commodity exporters to China (other than the U.S.) to construct an instrument for changes in Chinese demand. The instrument $\Delta EPA_{oit}$, is calculated as follows:

$$\Delta EPA_{oit} = \sum_j \frac{A_{ijt}}{A_{ujt}} \frac{\Delta E_{ocjt}}{A_{it}/100} \qquad (3.2)$$ [8]

This expression (3.2) is very similar with the expression (3.1). The only difference is that in equation (3.2) we use $\Delta E_{ocjt}$ instead of $\Delta E_{ucjt}$ as in other 10 high Chinese exporting countries' agricultural export change instead of U.S. agricultural export change to China[9]. The identifying assumption is that China's internal demand shocks, for example, its own economic growth with rising living standard, changing structure of food demands, short of land-intensive

[8] In Autor, Dorn and Hanson's paper, they use 10-year lagged employment levels because contemporaneous employment of a region is affected by anticipated China trade. However, we are only using the same period of acres harvested here under the assumption that planting decisions made in 1997 are independent of China's future import growth. Also, annual decision for farmers tend to be more contemporaneous compared with manufacturing hiring period.

[9] The subscript U stands for the U.S. while O stands for other 10 countries.

commodities compared with labor-intensive commodities, not U.S. specific positive supply and productivity shocks leading to this outcome.

As we are using a two stage least square model (2SLS), the first stage regression is constructed as follow:

$$\Delta EPA_{uit} = \alpha_{it} + \beta \Delta EPA_{oit} + u_{it} \qquad (3.3)$$

**Section 3.3 Primary specification**

In the second stage, we estimate the effects of changes in exports to China per acre on U.S. local agricultural outcomes using the following equation:

$$\Delta A_{it}^{e} = \beta_1 \Delta EPA_{uit} + \varepsilon_{\boldsymbol{it}} \qquad (3.4)$$

In equation (3.4), $\Delta A_{it}^{e}$ is the change in the local outcome variable in county $i$ over different time intervals over 5, 10 and 15 years. The main local outcomes we consider are total acres harvested, total cropland acres, estimated value of land and buildings, government payment and value of crops. Each specification is estimated using two-stage least squares (2SLS) by instrumenting the change U.S. exports per acre harvested in county $i$ ($\Delta EPA_{uit}$) with the change in other 10 countries' exports to China ($\Delta EPA_{oit}$). Equation (3.4) may also contain a vector of control variables $\boldsymbol{X}_{it}$ that might independently affect the local outcome of interest[10].

**Section 4. Data**

Our econometric exercises combine data from 2 sources. The U.S. Census of Agriculture provides information on U.S. county-level outcomes. U.N COMTRADE provides bilateral trade flow data on Chinese imports from the United States and from 10 other large agricultural importers.

[10] The control variables we use are population and net cash farm income. Regression results with control variables are not reported in the results section, as the main results are not changed much with the control variables added.

### 4.1. U.S. County level data

We use data from U.S. Census of Agriculture from 1997 to 2012 based on a five-year interval from the Census Quick Stats Database (USDA, 2017). We selected the group of field crops with all commodities available at county level in the years 1997, 2002, 2007 and 2012.

In general, within the combined data from these four years' U.S. Agricultural Census, there are in total 50 States, 3050 Counties[11], and 42 kinds of commodities. Due to the absence of the electronic editable version data of U.S Census of Agriculture before 1997, we use data from ICPSR (ICPSR, 2016) for the data of U.S. Census of Agriculture for the year of 1982 and 1992. There are also in total 50 States, 3077 counties. The major commodities and the number of counties growing each crop are listed in Table 4.1. In general, there are 40 different types of agricultural commodities[12] with acres harvested data in at least one of the six census years. While in the year of 1982 and 1992, there are only 14 commodities' data available, our major analysis is performed only starting from 1997, and most of the major commodities are covered within these 14 commodities.

One challenge inside the census data, is that in order to avoid disclosing the data of individual farmer. These cells, denoted with a "D" in the dataset, typically account for a small share of the total acres harvested. However, we need a complete dataset to do our calculations. To address this problem, we calculated total acres harvested for each commodity as measured in the county level data (treating the "D"s as zero). For each commodity, the differences between this total acre harvested and the reported value of acres harvested for the U.S. of each crop, are the acres that have been suppressed. Then we allocate this difference equal proportionally across the counties with data suppressed for that crop.

[11] 50 states include Alaska and Hawaii, but exclude Washington, DC. For counties, the Parishes from Louisiana and Boroughs from Alaska are treated as counties.
[12] The complete commodity list is: Barley, Beans, Buckwheat, Canola, Corn, Cotton, Dill, Emmer&Spelt, Flaxseed, Guar, Hay, Haylage, Herbs, Hops, Jojoba, Legumes, Lentils, Millet, Mint, Mustard, Oats, Peanuts, Peas, Popcorn, Rapeseed, Rice, Rye, Safflower, Sesame, Sorghum, Soybeans, Sugar beets, Sugarcane, Sunflower, Sweet Rice, Taro, Tobacco, Triticale, Wheat and Wild Rice.

Table 4.1: Major Commodity Types and Number of Counties with Production

Table 4.1: Major Commodity Types and Number of Counties with Production

| Commodity | 1982 | 1992 | 1997 | 2002 | 2007 | 2012 |
|---|---|---|---|---|---|---|
| Barley | 516 | 484 | 837 | 778 | 702 | 678 |
| Beans | 81 | 82 | 255 | 296 | 230 | 244 |
| Corn | 1177 | 2315 | 2460 | 2438 | 2438 | 2469 |
| Cotton | 428 | 485 | 514 | 509 | 469 | 501 |
| Hay | NA | NA | 2968 | 3025 | 3020 | 3003 |
| Haylage | NA | NA | 1982 | 2034 | 2312 | 2384 |
| Oats | 993 | 971 | 1726 | 1674 | 1427 | 1314 |
| Peanuts | 203 | 166 | 241 | 242 | 214 | 230 |
| Rye | NA | NA | 514 | 621 | 462 | 429 |
| Sorghum | 709 | 663 | 1027 | 1086 | 950 | 943 |
| Soybeans | 1776 | 1646 | 1811 | 1768 | 1738 | 1878 |
| Sunflower | 138 | 107 | 249 | 313 | 262 | 250 |
| Tobacco | 403 | 387 | 463 | 451 | 341 | 291 |
| Wheat | 2397 | 2199 | 2198 | 2123 | 2058 | 2146 |

Notes: NA stands for not available in the year of 1982 and 1992.

### 4.2. Other major exporters of field crops to China

Autor, Dorn and Hanson use data on imports from 10 non-U.S. high-income countries to construct their instrument for a Chinese supply shock to the U.S. In my case, I construct the instrument for a Chinese demand shock using export data from 10 large (non-U.S.) agricultural exporters. China's agricultural imports are highly concentrated in several commodities, notably soybean, cereal, cotton and oilseed. As of 2015, five countries U.S. (21.2%), Brazil (17%), Australia (6.9%), Canada (4.5%) and Argentina (4.4%) jointly accounted for more than 53% of China's total agricultural imports (China International Agricultural Product Trade Statistical Yearbook, 2015). We choose these 10 countries by taking the rank of their export value to China from 1997 to 2017 within these top products that China imports the most.

Table 4.2: China's Agricultural Import Concentration, 1997 – 2017

| Major Products | Top 5 Import Sources | Top 5 Concentration |
|---|---|---|
| Rice | Thailand (46.1%), Vietnam (38.9%), Pakistan (11.1%), Cambodia (2.1%), Laos (0.9%) | 99.1% |
| Wheat | U.S. (34.2%), Australia (31.7%), Canada (29.6%), Kazakhstan (2.3%), France (2.1%) | 99.9% |
| Corn | U.S. (64.0%), Ukraine (27.2%), Laos (3.1%), Thailand (1.6%), Bulgaria (1.2%) | 97.1% |
| Cotton | U.S. (37.0%), India (22.1%), Australia (13.4%), Uzbekistan (8.1%), Brazil (4.2%) | 84.8% |
| Soybean | Brazil (41.2%), U.S. (40.9%), Argentina (14.4%), Uruguay (2.5%), Canada (0.9%) | 99.9% |
| Sunflower (Oilseed) | U.S. (63.0%), Kazakhstan (23.0%), Chile (5.3%), Argentina (2.6%), Australia (1.5%) | 95.4% |

Source: UN Comtrade

For the export data, we use data from the UN Comtrade Database on U.S. and other countries exports to China at the six-digit Harmonized System (HS) commodity level. According to the percentages shown in Table 4.2, the 10 countries I use to construct the instrument are Argentina, Australia, Brazil, Canada, India, Kazakhstan, Thailand, Ukraine, Uruguay and Vietnam.

Meanwhile, Table 4.3 shows the comparison between the U.S. and these other 10 countries' trade of agricultural products with China, especially their exports to China (Table 4.3). The first column of Table 4.3 shows the value of annual U.S. agricultural exports to China for the years of 1997, 2002, 2007 and 2012. The volume of U.S. imports from China was substantially smaller than the volume of exports throughout these years, and the growth of exports outpaced the growth of imports. The primary change in U.S. - China trade during our sample period is thus the dramatic increase of U.S. exports. While at the same time, U.S. exports to the rest of the World only increased 98% in 20 years. Table 4.3 also summarizes the trade flow from the same importers to the selected 10 countries that have a long history involved. Like the U.S., these countries also experienced a dramatic increase of export to China, and a more modest growth of export to the rest of the World, which makes it reasonable to use these countries to construct as instrumental variable.

Table 4.3. Value of Trade of Agricultural Products with China 1997 – 2002

| | Trade with China | | Trade with Rest of World |
|---|---|---|---|
| | Exports to China | Imports from China | Exports to Rest of World |
| United States | | | |
| 1997 | 1,605,346 | 764,459 | 62,875,746 |
| 2002 | 1,988,743 | 1,166,220 | 55,556,525 |
| 2007 | 8,376,490 | 3,275,556 | 87,345,940 |
| 2012 | 25,917,251 | 4,801,774 | 124,429,978 |
| Growth 1997-2012 | 1514% | 528% | 98% |
| Other 10 Countries | | | |
| 1997 | 3,157,777 | 449,342 | 75,210,883 |
| 2002 | 3,927,219 | 959,171 | 75,516,939 |
| 2007 | 14,354,645 | 2,393,332 | 153,059,372 |
| 2012 | 42,433,976 | 5,110,916 | 267,821,318 |
| Growth 1997-2012 | 1244% | 1037% | 256% |

Source: USDA, Economic Research Service analysis of data from USDA, Foreign Agricultural Service, Global Agricultural Trade System.
Notes: Other 10 countries are: Argentina, Australia, Brazil, Canada, India, Kazakhstan, Thailand, Ukraine, Uruguay and Vietnam. All units are in 2012 dollars.

### 4.3. County-level exposure to growing Chinese imports

With all the data mentioned above available, each county's exposure to growing Chinese field crop demand can now be calculated. In order to provide a sense of the "China Shock" across the U.S. counties, this section shows the descriptive analysis of the U.S. export to China exposure for the time period of 1997 to 2012, which is also our main estimation time period.

Table 4.4 shows descriptive statistics for $\Delta EPA_{uit}$ across the 15-year time periods of 1997 to 2012. In the median county, the 15-year growth of exports to China was 0.21 dollars per 100 acres (or 21 dollars per acre) from 1997 to 2012.[13] Panel B of the table also summarizes changes in export exposure per acre among the top, median and bottom counties. The top counties from 1997 to 2012 have an increase above 2 dollars per hundred acres in terms of growing export exposure to China. The counties that have 0 export exposure only produced

[13] We report data in dollars per hundred acres in order to aid the interpretation of (otherwise tiny) regression coefficients. This can complicate slightly discussions of summary statistics but we view hundreds of acres as the preferable choice of units.

commodities that did not have changes in exports within the 15-year period. And that essentially means those commodities that have not been exported to China like Amaranth, Camelina and Miscanthus.

Table 4.4: Descriptive Statistics for Growth of Export to China Exposure per 100 Acres

**Panel A. Percentiles**

| 90th percentiles | 75th percentiles | 50th percentiles | 25th percentiles | 10th percentiles |
|---|---|---|---|---|
| 1.144 | 0.915 | 0.210/0.210 | 0.036 | 0.017 |

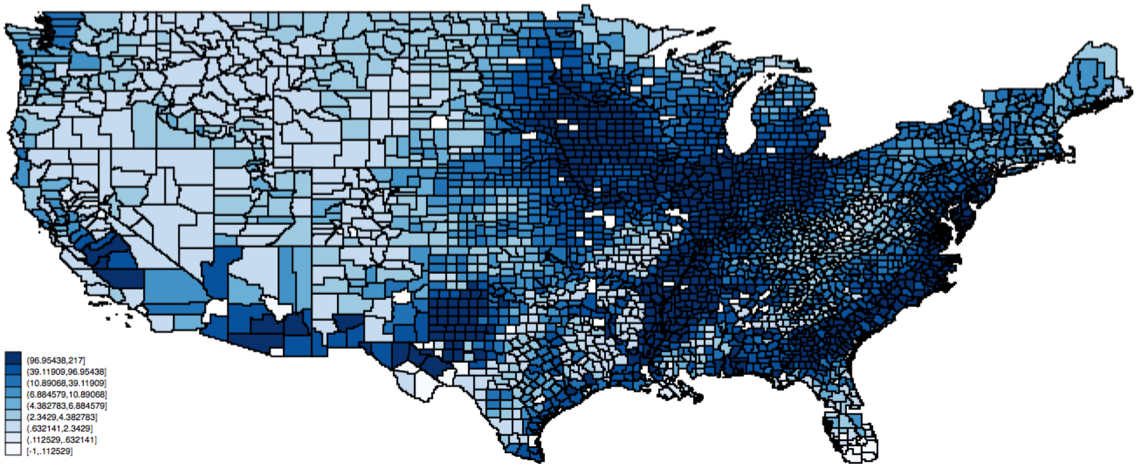
**Panel B. Largest and smaller values among all counties**

| | | | | |
|---|---|---|---|---|
| *Top 5* | | | | |
| Dare, NC 2.168 | Culberson, TX 2.161 | Martin, TX 2.037 | Howard, TX 2.024 | Borden, TX 2.014 |
| *Median* | | | | |
| McDuffie, GA 0.2104 | Baylor, TX 0.2101 | | | |
| *Bottom 5* | | | | |
| Muscogee, GA 0 | Barnstable, MA 0 | Queens, NY 0 | Palm Beach, FL -0.00002 | Glades, FL -0.0004 |

Notes: Table reports 15-year values of (Δexports from US to China)/100 acres harvested, in US$, for US counties over the period 1997-2012.

Additionally, in order to gain a more direct view of the whole U.S. picture in terms of the exposure of exports to China, we illustrate a map of all U.S. mainland counties across the 15-year period of 1997-2012 (Figure 4.1). All counties are colored in nine same scales of blue in both maps based on nine quantiles of the whole estimation, as higher exposure comes with darker blue.

Figure 4.1: U.S. County Map of $\Delta EPA_{uit}$ across 1997-2012




Notes: The map shows the depth of U.S. county level exposure to rising Chinese imports demand, as measured by variable $\Delta EPA_{uit}$. $\Delta EPA_{uit}$ is defined in equation 3.1.

Also, based on the maps provided, we also show the top commodities that have the highest increase in exports to China. As we can see soybeans is the most increased commodity in absolute dollars across these 15 years. It has been increasing by almost 15 billion dollars since 1997 to 2012. While Corn is the commodity that comes with the highest percentage increase. Some of the non-major commodities have shown quite high percentage increases like jojoba and guar due to their low trade amount back in the year of 1997. While major crops like cotton, corn and wheat have seen significant increases in absolute dollars. It's also reflected on the map in Figure 4.1 as major soybeans, cotton and corn growing states are having dark blues.

Table 4.5: Top 5 Commodities in Export Increase, 1997-2012, in value and in percentages

| Top Commodities | Increase, in Value ($US billions) | | Increase, in Percentages | |
|---|---|---|---|---|
| 1. | Soybeans | 14.69 | Corn | 974,953% |
| 2. | Cotton | 3.00 | Tobacco | 153,803% |
| 3. | Corn | 1.66 | Hay | 212,612% |
| 4. | Wheat | 0.19 | Jojoba | 19,072% |
| 5. | Hay | 0.09 | Guar | 7,284% |

### 4.4. Theories of change

Increases in the Chinese import demand for particular crops should have led to increases in global demand for the particular crops that China imports heavily. These relative demand increases should have increases the relative prices and relative quantities demanded of field crops that China imports intensively, relative to other field crops. The research question in this paper is whether these price and quantity effects were large enough to affect measurable outcomes as they are observed in the U.S. agricultural census. In this section we offer hypothetical causal chains to indicate likely mechanisms through which growing import demand from China would affect the six variables we study.

The effects on *total cropland acres*, as measured in the agricultural census, are likely to operate primarily through the channel that increasing quantities require more acreage in cropland. Note that this variable does not change with crop-switching decisions, it measures (relative) growth in the total acres in cropland.

Both increases prices and increased quantities demanded of the crops with growing demand from China should affect the *value of crops* reported in agricultural census. Rising prices would make existing production more valuable, while increasing production would also increase the total value of crops through an extensive margin.

We expect increasing demand from China to raise the *value of agricultural land and buildings* through two primary mechanisms. First, existing land should become more valuable as its output is more heavily demanded. Second, there may also be investments in buildings that arises as a result of more overall activity.

We would expect growth in total cropland acres to translate into growth in *harvested cropland acres*. Specifically, we expect that counties that see growing export exposure to China should see increases in the total number of acres harvested.

To the degree that growing imports by China raises the prices of particular commodities, we would expect government subsidy payments to fall in those commodities. Thus we predict that counties that are more exposed to growing Chinese imports demands would see (relative) reductions in *total government payments* and *average government payments per farm*.

## Section 5. Results

Upon calculating the values of Chinese export exposure and the instrumental variable of $\Delta EPA_{uit}$ and $\Delta EPA_{oit}$, it is now possible to estimate a causal relationship between Chinese export exposure and local agricultural outcomes such as land values, government payment and total acres harvested. This chapter contains a discussion of the regression results across time periods and regression problems.

### Section 5.1. First Stage and OLS Results for Main Estimates, 1997-2012

We first have the first stage results of the 2SLS regression and the OLS regression results for the time period of 1997 to 2012. Instead of our baseline model only, we also show our regression results with a squared term of export exposure added to the equation with the intention to check for non-linear results.

Table 5.1: Exports to China and Percentage Change of Multiple Agricultural Outcomes on U.S. Counties, 1982-1997: First-Stage Estimates

Panel A. Baseline Model

| | EPAUS9712 |
|---|---|
| | (1) |
| EPAOTHER9712 | 0.563*** |
| | (0.005) |
| N | 2987 |
| R square | 0.811 |
| F-Stat | 12810.23 |

Panel B. Model with Squared Terms

| | EPAUS9712 | EPAUS9712SQ |
|---|---|---|
| | (1) | (2) |
| EPAOTHER9712 | 0.563*** | 0.990*** |
| | (0.005) | (0.008) |
| EPAOTHER9712SQ | -0.055*** | -0.060*** |
| | (0.001) | (0.001) |
| N | 2987 | 2987 |
| R square | 0.929 | 0.872 |
| F-Stat | 19610.96 | 10119.11 |

Notes: Dependent Variable (EPAUS9712) is the change in export exposure per 100 acres in the U.S. in USD between the year of 1997 and 2012. Independent Variable (EPAOTHER9712) is the instrumented export exposure per acre in other 10 large agricultural exporters to China (Argentina, Australia, Brazil, Canada, India, Kazakhstan, Thailand, Ukraine, Uruguay and Vietnam) in USD between the year of 1997 and 2012.

Table 5.2: Exports to China and Percentage Change of Multiple Agricultural Outcomes on U.S. Counties, 1997-2012: OLS Estimates

Panel A. Base Model

| | ΔTC (1) | ΔVC (2) | ΔEMVB (3) | ΔAH (4) | ΔGPTR (5) | ΔGPAPF (6) |
|---|---|---|---|---|---|---|
| (Δexports to China from U.S.)/ | 0.261*** | 0.111*** | 0.109*** | -0.075*** | -0.358*** | -0.226*** |
| 100 acres | (0.012) | (0.017) | (0.014) | (0.013) | (0.028) | (0.021) |
| N | 2917 | 2942 | 2983 | 2954 | 2941 | 2943 |
| R square | 0.142 | 0.015 | 0.020 | 0.010 | 0.052 | 0.038 |

Panel B. Model with Squared Terms

| | ΔTC (1) | ΔVC (2) | ΔEMVB (3) | ΔAH (4) | ΔGPTR (5) | ΔGPAPF (6) |
|---|---|---|---|---|---|---|
| (Δexports to China from U.S.)/ | 0.481*** | 0.497*** | 0.334*** | 0.063*** | -0.909*** | -0.480*** |
| 100 acres | (0.037) | (0.052) | (0.044) | (0.042) | (0.089) | (0.066) |
| Squared Terms | -0.167*** | -0.291*** | -0.170*** | -0.104 | 0.416*** | 0.192*** |
| | (0.027) | (0.037) | (0.031) | (0.030) | (0.064) | (0.047) |
| N | 2917 | 2942 | 2983 | 2954 | 2941 | 2943 |
| R square | 0.153 | 0.035 | 0.030 | 0.014 | 0.065 | 0.044 |

Notes: Dependent variables are total cropland acres (TC), value of crops (VC), estimated market value of agricultural land and buildings (EMVB), total acres harvested (AH), government payments total received (GPTR) and government payments average per farm (GPAPF),. And N = Counties with data available. The 15-year difference for all dependent variables are logged.

*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

The first stage results suggest there exist a consistent relationship between export exposure per acre in the U.S and the instrumented export exposure per acre in the other 10 large exporters to China. The value of $R^2$ is 0.811, indicating that our instrument is very strong. However, our OLS estimates are still as weak as our 2SLS main results. Both the coefficients and R square numbers are relatively small. Thus, our estimates explain that the China shock did exist and tend to be strong between 1997 and 2012. However, it did not affect U.S. local agricultural outcomes very much compared with the other shocks that was happening at the same time.

**Section 5.2. 2SLS estimates for 1997-2012**

Table 5.3: Exports to China and Percentage Change of Multiple Agricultural Outcomes on U.S. Counties, 1997-2012: 2SLS Estimates

| | ΔTC | ΔVC | ΔEMVB | ΔAH | ΔGPTR | ΔGPAPF |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| (Δexports to China from U.S.)/ | 0.247*** | 0.087*** | 0.069*** | -0.103*** | -0.377*** | -0.249*** |
| 100 acres | (0.013) | (0.019) | (0.016) | (0.015) | (0.031) | (0.023) |
| N | 2917 | 2942 | 2983 | 2954 | 2941 | 2943 |
| R square | 0.142 | 0.014 | 0.017 | 0.009 | 0.052 | 0.038 |

Notes: Dependent variables are total cropland acres (TC), value of crops (VC), estimated market value of agricultural land and buildings (EMVB), total acres harvested (AH), government payments total received (GPTR) and government payments average per farm (GPAPF). And N = Counties with data available. The 15-year difference for all dependent variables are logged.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

There are six different agricultural outcomes we study in this main estimation. Each column of Table 5.1 provides results from estimation on equation (3.3) and (3.4) together using two-stage least squared method (2SLS). Despite the substantial growth in U.S. exports of field crops to China, our estimates show small but statistically significant effects of Chinese import growth on U.S. production outcomes. Over the period of 1997-2012 we find that growing Chinese import demand led to small but significant increases in the value of U.S. crop production, total U.S. cropland acres, the estimated market value of agricultural land and buildings, small but significant decreases in government payments to farmers and total field crop acres harvested.

The coefficient of 0.069 in column 1 indicates that an exogenous $1 rise in a county's export exposure per 100 acres over 15-year period is predicted to increase the estimated market value of agricultural land and buildings by 0.069 percent, increase the total cropland acres by 0.247 percent and increase the value of crops sold by 0.087 percent. Also, the estimation shows Chinese import exposure would lead to decrease of 0.377 percent, 0.249 percent and 0.103 percent for total government payments received, average government payment per farm and total field crop acres harvested respectively.

We find statistically significant but weak evidence that Chinese import demand affected all of the variables we study. The distribution of $\Delta EPA_{uit}$ has a strong right skew, with the most heavily treated counties affected by strongly by China while most other counties are not.[14] This leads us to wonder whether there are non-linear effects of the treatment. In order to investigate this possibility we estimate a model with $\Delta EPA_{uit}$ and $(\Delta EPA_{uit})^2$ as explanatory variables. (Both these variables are instrumented by $\Delta EPA_{oit}$ and $(\Delta EPA_{oit})^2$ in the first stage). These results are reported in table 5.4

Table 5.4: Exports to China and Percentage Change of Multiple Agricultural Outcomes on U.S. Counties, 1997-2012: 2SLS Estimates with Squared Terms

| | ΔTC | ΔVC | ΔEMVB | ΔAH | ΔGPTR | ΔGPAPF |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| (Δexports to China from U.S.)/ | 0.588*** | 0.743*** | 0.538*** | 0.065 | -0.422 | -0.305 |
| 100 acres | (0.179) | (0.243) | (0.204) | (0.198) | (0.415) | (0.307) |
| Squared Terms | -0.247* | -0.472*** | -0.338*** | -0.121 | 0.0323 | 0.041 |
| | (0.133) | (0.179) | (0.151) | (0.146) | (0.307) | (0.226) |
| N | 2917 | 2942 | 2983 | 2954 | 2941 | 2943 |
| R square | 0.151 | 0.027 | 0.020 | 0.013 | 0.053 | 0.040 |

Notes: Dependent variables are total cropland acres (TC), value of crops (VC), estimated market value of agricultural land and buildings (EMVB), total acres harvested (AH), government payments total received (GPTR) and government payments average per farm (GPAPF). And N = Counties with data available. The 15-year difference for all dependent variables are logged.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

All six variables have sign switches across level and squared terms, indicating diminishing marginal effects of the treatment variable. It is somewhat difficult to interpret these results as regression coefficients alone; one key question is whether the estimated treatment effct is stable across the sample, especially among the heavily treated counties. To illustrate this we calculate treatment effects at various points in the distribution of $\Delta EPA_{uit}$. These results are reported in Table 5.5.

[14] The skewness of the treatment variable is also a key reason for the low $R^2$ values, as there is considerable variation in all of our outcomes variables among the lightly treated counties that goes unexplained.

Table 5.5: Percent change in agricultural outcomes for selected counties, 1997-2012

| Change in export exposure | County | %ΔTC | %ΔVC | %ΔEMVB | %ΔAH | %ΔGPTR | %ΔGPAPF |
|---|---|---|---|---|---|---|---|
| 25th Percentile | Rolette, ND | 2.11 | 2.65 | 1.92 | 0.22 | -1.53 | -1.11 |
| Median | McDuffie, GA | 11.28 | 13.54 | 9.82 | 0.83 | -8.73 | -6.23 |
| 75th Percentile | Crawford, KS | 33.12 | 28.47 | 20.93 | -4.18 | -35.90 | -24.47 |
| 90th Percentile | McLean, IL | 34.94 | 23.22 | 17.31 | -8.40 | -44.05 | -29.53 |
| Maximum | Dare, NC | 11.38 | -60.77 | -42.22 | -42.78 | -76.31 | -46.85 |

Notes: These percentage changes are calculated by these counties' $\Delta EPA_{uit}$ multiplied by the coefficients estimated from Table 5.1 in 1997-2012.

The estimated effects of China's import demand growth on total cropland are consistently positive, but highly non-linear, peaking near the 90th percentile. The calculated sign on the treatment effect is also stable for *government payments total received*, and average government payments per farm. In the case of the subsidy payment variables, estimated treatment effects are monotonically related to the degree of change in export exposure to China. For the other three variables – value of crops, market value of land and buildings, and acres harvested - we see that the non-linear effects lead to changes in the sign of the treatment effect within the distribution. The unstable sign pattern makes it extremely difficult to make causal claims about the effect of Chinese demand growth on these variables. These arguments are bolstered by visual inspection of scatterplots reported in Appendix B.

### Section 5.3. Estimates over 10-year Windows

Even though we use the 15-year interval as our main results, it is still necessary to look at the 10-year time period influence as China's entrance of the WTO[15] did not show the expected increasing influence. As the main estimations don't show expected results, the 10-year period estimations will also serve as a robustness check. Based on Figure 1.1 we can observe a clear increase of U.S. agricultural exports to China as well as China's share of the total U.S. agricultural exports between the year of 2002 and 2003.

[15] China joined the WTO in Sep 2001.

Table 5.6: Effects of export exposure to China on agricultural outcomes: 2SLS Estimates

a. 2002-2012

| | ΔTC | ΔVC | ΔEMVB | ΔAH | ΔGPTR | ΔGPAPF |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| (Δexports to China from | 0.231*** | 0.241*** | 0.101*** | -0.037*** | -0.121*** | -0.191*** |
| U.S.)/acre | (0.011) | (0.015) | (0.014) | (0.012) | (0.024) | (0.021) |
| N | 2973 | 2939 | 2982 | 2980 | 2876 | 2879 |
| R square | 0.148 | 0.089 | 0.027 | 0.003 | 0.006 | 0.022 |

b. 1992-2002

| | ΔTC | ΔVC | ΔEMVB | ΔAH | ΔGPTR | ΔGPAPF |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| (Δexports to China from | -0.506*** | -0.007*** | 1.290*** | -6.23*** | 0.814*** | 0.517*** |
| U.S.)/acre | (0.084) | (0.149) | (0.121) | (0.495) | (0.284) | (0.240) |
| N | 2907 | 2970 | 2975 | 2770 | 2849 | 2853 |
| R square | 0.008 | 0.001 | 0.049 | 0.004 | 0.013 | 0.009 |

Notes: Dependent variables are total cropland acres (TC), value of crops (VC), estimated market value of agricultural land and buildings (EMVB), total acres harvested (AH), government payments total received (GPTR) and government payments average per farm (GPAPF). And N = Counties with data available. The 15-year difference for all dependent variables are logged.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

All our 10-year estimates are statistically significant, indicating export exposure to China does have significant influence over all our agricultural outcomes but still, it only explains for small effect from China's growing demand. Compared with the 15-year results from 1997 to 2012 (Table 5.1), the 10-year results from 2002 to 2012 (Table 5.4.a) shows a little bit larger effect in the percentage change of estimated value of agricultural land and buildings (from 0.069 to 0.101), about three times larger effect in change of value of crops sold (from 0.087 to 0.241). It also explains a less effect for both government payment outcomes and total field crops acres harvested. Our estimates also imply a similar effect for total cropland acres for both 10-year and 15-year time periods (0.247 and 0.231).

Panel b of Table 5.4 shows the pre-exposure 10-year period for 1992-2002. The estimates suggest that U.S. counties with crops are more exposed to increased Chinese import demand, the government payments tend to decrease. While the total cropland acres and value of crops are changing from decreasing to increasing. Market value of agricultural land and buildings are increasing more slowly, and the total field crops acres harvested are decreasing more slowly.

In general, both 10-year (2002-2012) and 15-year (1997-2012) time periods are suggesting China's growing demand has a significant positive effect over market value of agricultural land and buildings, total cropland acres and value of crops, a significant negative effect for government payments and total field crops acres harvested. However, although all our estimation results are statistically significant, the R square values show that Chinese imports explain only a small part of the variation in outcome variables. Even though our first-stage and OLS results suggest that the China shock is strong, it is hard to determine that more exposure to Chinese agricultural imports would lead to more impact over U.S. local agricultural outcomes.

Autor, Dorn and Hanson's estimates indicate that increases in imports from China can explain one-quarter of the contemporaneous aggregated decline in U.S. manufacturing employment. Our estimations, on the other hand, explain far less of the observed variation. Possible reasons could be from a number of other large shocks affecting U.S. agriculture over the period, including but not limited to other trade policy changes, the U.S. ethanol boom, growing competition from exporters such as Brazil and technological changes. The noise associated with these other shocks appears to have been large relative to the effects of growing demand from China.

## Section 6. Conclusion

A prominent literature has demonstrated that the supply shock associated with the entry of China into global markets for manufactured goods had detrimental impacts on U.S. workers employed in associated import competing industries. The estimated effects of this supply shock were large, both in economic magnitude and in terms of statistical significance. In this paper we estimate the effects of the demand shock associated with China's entry into the global market for field crops on six outcomes at the U.S. county level. We estimate effects on these outcomes that are large in an economic sense, but in a statistical sense they are much weaker than is the case for manufacturing. For five of the six variables, the China demand shock explains less than 10 percent of the observed changes in the outcome variables, and less than 5 percent of the variation in four of the six variables. We interpret the absence of a robust influence for the China shock as evidence that the cumulative effects of other shocks occurring during this period were much more important. These other shocks would include: the ethanol boom, growing urban pressure on agricultural lands, changes in agricultural policies, technological changes, global trade liberalization in agricultural markets, and growing competition from South America in global agricultural markets.

The most robust evidence we find is that the China demand shock increased total cropland acres. Roughly 15 percent of the county-level changes in cropland acres from 1997-2012 can be attributed to increased demand from China. The growth in cropland acres we attribute to China is quite large – we estimate that total cropland acres are 11 percent higher in the median county than would have been the case without China. Our data show an overall decrease in cropland acres during the period of study, but the effects of growing demand from China offset this overall trend.

The evidence that growing Chinese demand affected government payments to farmers is somewhat less robust, but still meaningful. Approximately five percent of the overall variation in subsidy payments can be attributed the China shock. In the median county we estimate that the government payments were almost 9 percent lower because of the China shock. Government payments were increasing during 1997-2012, but counties specializing in crops experiencing a China shock saw slower growth in government payouts.

We also found some evidence that counties that were more heavily exposed to the China shock saw relatively larger increases in the value of their crops, in the value of agricultural land and buildings and in average government payments per farm, but the evidence in favor of these conclusions is statistically weak. $R^2$ values in these regressions were below 0.05, even after the inclusion of squared terms in regression. Even though the signs of the squared terms were offsetting, the implied effects of the China shock on these variables were stable across the sample. We also attempted to estimate effects of the Chinese demand shock on total acres harvested at the county level. The sign on the estimated effects of Chinese demand varied over the sample, making it difficult to quantify an effect of China on total acres harvested.

We conclude that the results of China on U.S. agricultural outcomes are more difficult to observe than are the effects of the effects on U.S. manufacturing workers. In all likelihood, this difficulty comes from two main sources. First, the relevant agricultural markets were subject to other large shocks during this period. Second, the relative ease of crop-switching in response to the China shock may have limited the consequences for U.S. farm outcomes. We estimate that the median county saw an increase of 11 percent in total cropland acreage because of the China shock, and a 9 percent reduction in total government subsidy payments. While we find quantitatively large effects of China on three other outcomes, these estimates are less robust statistically.

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## Appendix A. Concordance of Production and Trade data

Before the calculation of $\Delta EPA$ could be made, another challenge is to link the data of acres harvested from the census to the export data from UN Comtrade. The data of acres harvested from the census come with plain commodity names, while the commodities from UN Comtrade database are in six-digits HS codes. Thus, a rough mapping concordance between the census commodity names and their HS codes needs to be made in order to match the data from these two individual databases. All 40 commodities are listed below. Some of the commodities are as accurate as 6 digits while some major commodities like soybeans and wheat are as accurate as 4 digits

Table A.1: Mapping Concordance of Census Crops and their HS code

| Census Crops | HS Code | Census Crops | HS Code |
|---|---|---|---|
| Barley | 1003.90 | Oats | 1904.90 |
| Beans | 0708.20 | Peanuts | 1202.00 |
| Buckwheat | 1008.10 | Peas | 0708.10 |
| Canola | 1517.90 | Popcorn | 1904.10 |
| Corn | 1005.90 | Rapeseed | 1205.00 |
| Cotton | 5201.90 | Rice | 1006.00 |
| Dill | 0910.99 | Rye | 1002.90 |
| Emmer &Spelt | 1001.00 | Safflower | 1207.60 |
| Flaxseed | 1204.00 | Sesame | 1207.40 |
| Guar | 1302.32 | Sorghum | 1007.00 |
| Hay | 1214.90 | Soybeans | 1201.00 |
| Haylage | 1214.90 | Sugar beets | 1212.91 |
| Herbs | 1211/90 | Sugarcane | 1212.93 |
| Hops | 1210.00 | Sunflower | 1296.00 |
| Jojoba | 1515.90 | Sweet Rice | 1006.10 |
| Legumes | 0708.90 | Taro | 0714.40 |
| Lentils | 0713.40 | Tobacco | 2403.99 |
| Millet | 1008.21 | Triticale | 1008.60 |
| Mint | 1211.90 | Wheat | 1001.00 |
| Mustard | 1207.50 | Wild Rice | 1008.90 |

Note: Emmer & Spelt is combined with Wheat. Hay and Haylage share the same code.

**Appendix B. Scatter Plots of Main 2SLS Estimates with Squared Terms**

Figure B.1: Scatter Plot of Change in Export Exposure and Log Change in Total Cropland Acres

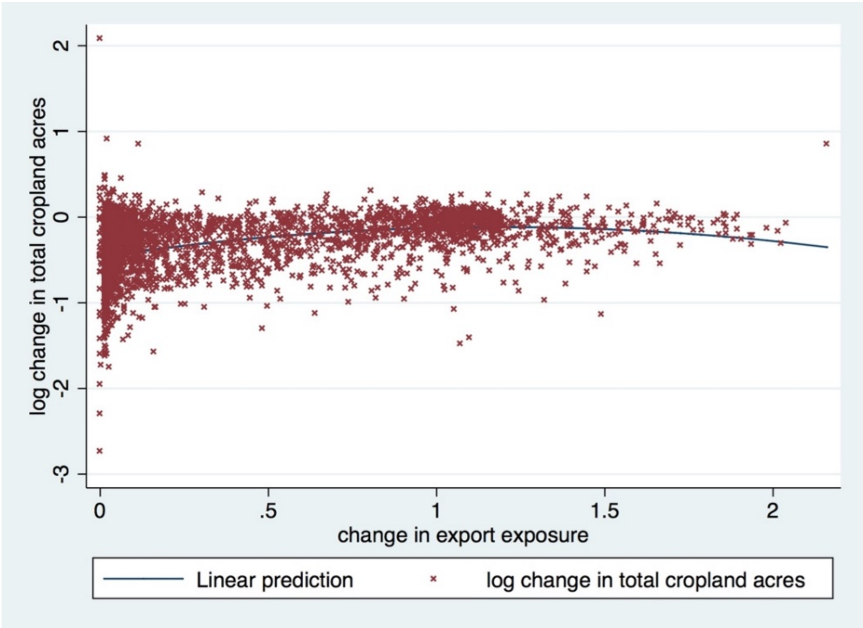


Figure B.2: Scatter Plot of Change in Export Exposure and Log Change in Value of Crop

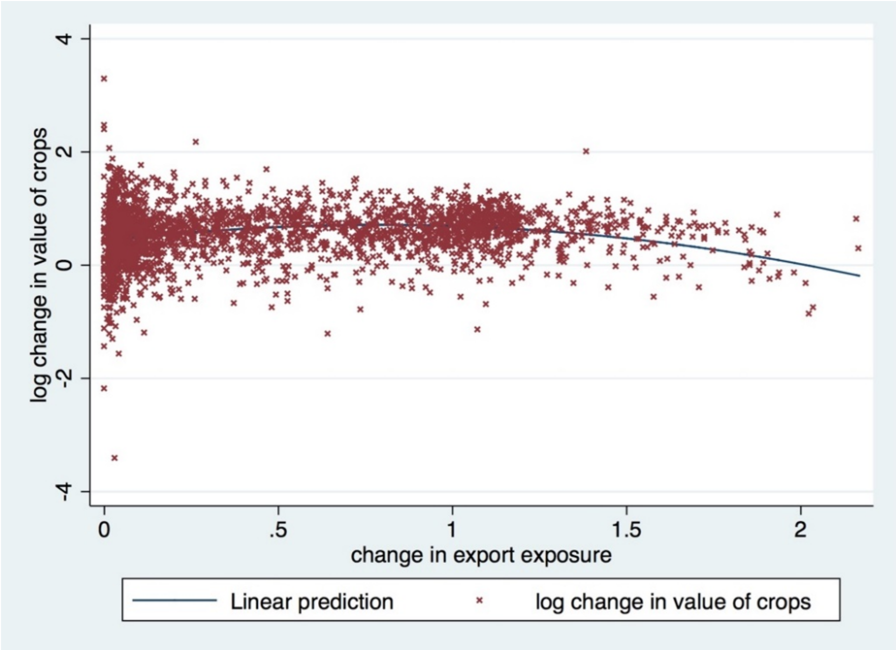

Figure B.3: Scatter Plot of Change in Export Exposure and Log Change in Value of Land and Buildings

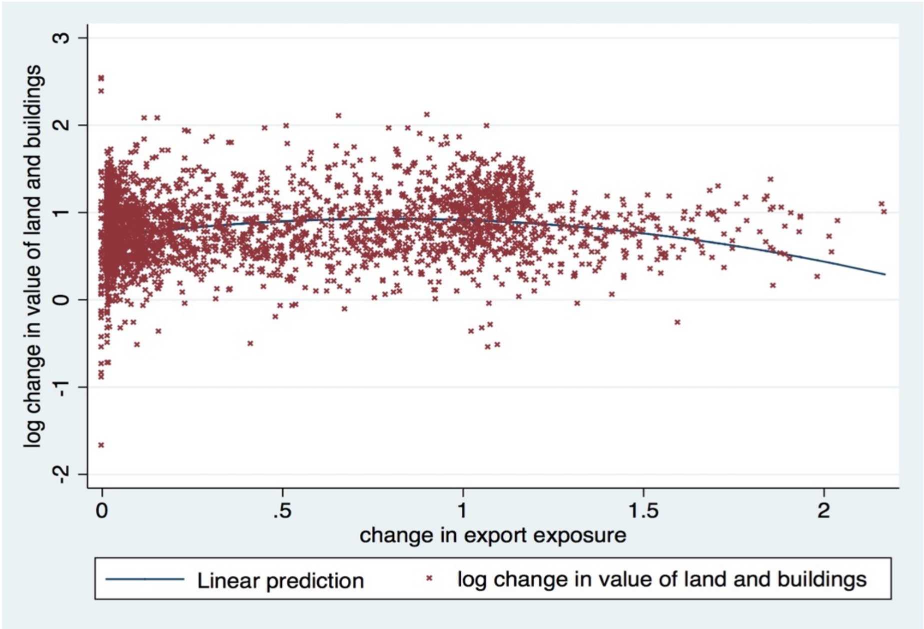


Figure B.4: Scatter Plot of Change in Export Exposure and Log Change in Acres Harvested

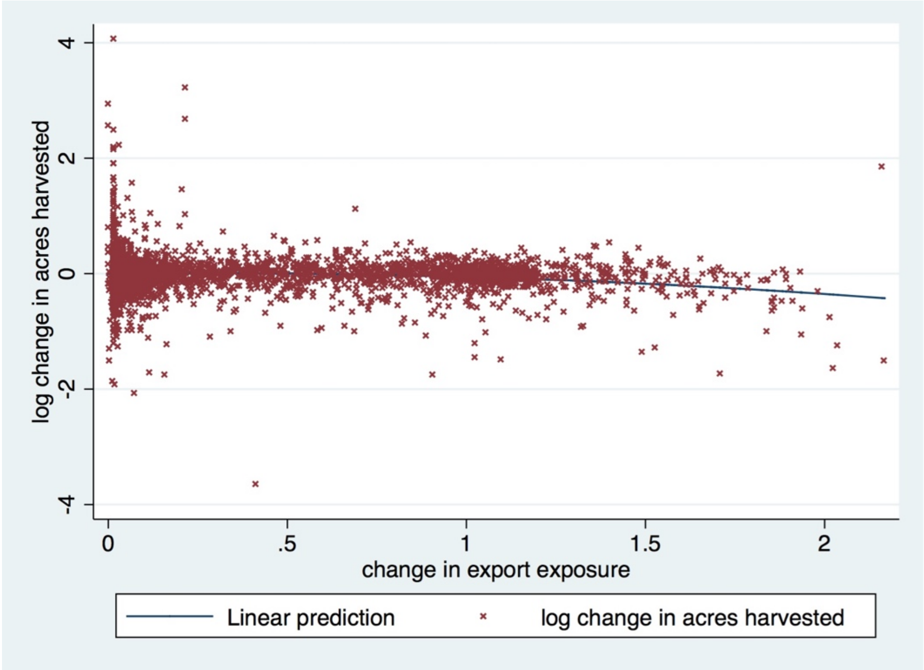

Figure B.5: Scatter Plot of Change in Export Exposure and Log Change in Government Payment Total Received

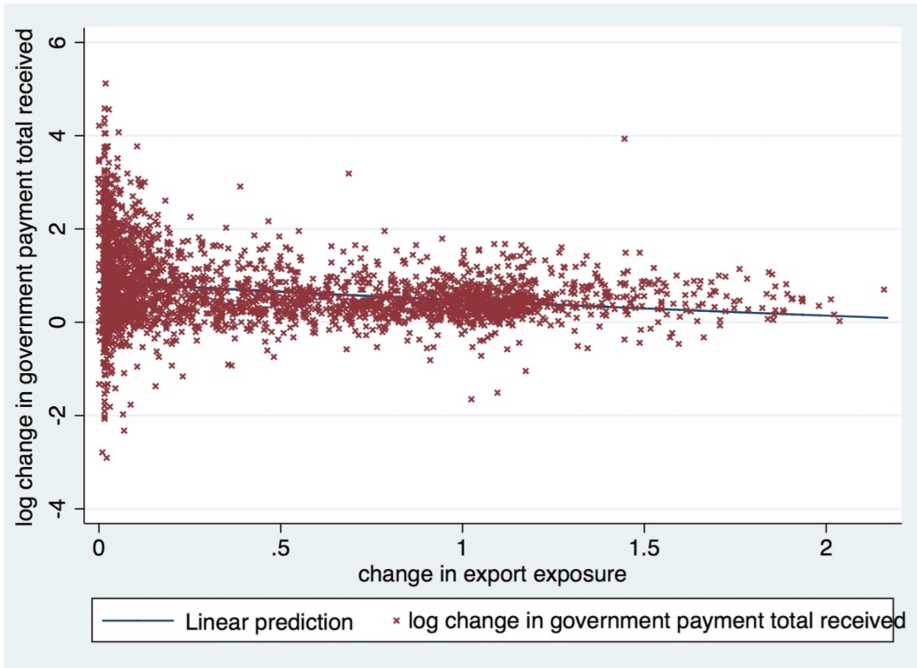


Figure B.6: Scatter Plot of Change in Export Exposure and Log Change in Government Payment Average per Farm