MEASURING THE IMPACT OF TRADE ON U.S. AGRICULTURE: A COUNTY-LEVEL EXPOSURE RATE CONSTRUCTION METHOD

by

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(Under the Direction of Cesar L. Escalante and Jeff D. Mullen)

ABSTRACT

Trade has been gaining negative attention throughout the past two decades. Stemming from the loss upon China's accession to the WTO in the U.S. manufacturing industry, combined with the recent trade disputes under the Trump administration, this dissertation aims to use the U.S. agriculture industry as an example, utilizing a well-known county-level exposure rate construction method to analyze how trade has been benefiting the local agricultural outcomes here in the United States. The dissertation consists of three Chapters. In the first Chapter, we use county-level data on agricultural outcomes and data on China's imports of U.S. agricultural commodities to study the effect of growing U.S. agricultural exports to China on U.S. county-level outcomes. We find that the "China Shock" had a reverse effect on U.S. agriculture than it did on the manufacturing sector. We show that exposure to exports that China demands strongly and positively impacts U.S. county-level farm and employment outcomes. In the second Chapter, we investigate what U.S. agriculture loses facing foreign import competition following similar trade exposure rate construction. We quantify how exposure to specific agricultural imports from the top 20 international suppliers in the world would affect the U.S. domestic county-level outcomes. We find that import exposure strongly and negatively impacts local farm-related employment and income, but the society's overall employment rate and income are positively connected with import exposure, indicating the existence of import competition. But the damage caused is likely absorbed by other industries and the aggregated influence from import exposure is beneficial. In the last Chapter, net trade exposure rates show less variation across U.S. counties compared with export and import exposures. The net trade exposure largely benefits U.S. county-level aggregated net farm income and agricultural employment share of the total working-age population, contradictory to what has been discovered in the manufacturing industry. The change in net trade exposure during the trade war periods, which was directly affected by the Trump administration's trade policies and its associated consequences, contribute to the achievement of their political targets and result in an increase in county-level voting shares in their favor.

INDEX WORDS: Trade, Agriculture, Exposure, County-level, China, Import, Export

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DEDICATION

This dissertation is dedicated to my parents, my wife, and my beloved Frenchies Fred and Hammer, for their endless support, love, and joy throughout these years.

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TABLE OF CONTENTS

Page

INTRODUCTION

CHAPTER

APPENDICES

LIST OF TABLES

LIST OF FIGURES

Page

INTRODUCTION

Summary

For more than two hundred years, economists have extolled the benefits of international trade. Although we regularly warn that—as with other forms of competition in a market economy—the associated market churn will make many better and some worse off, that part of the story has received far less attention. Until recently. Because its gains are diffuse and its harms are concentrated, international trade is a perfect target for public-choice style policy manipulation: the trade-exposed have much to gain by lobbying politicians to generate new barriers to trade, threatening the leading role the United States has played in reducing such barriers worldwide during the post-war period. And a series of economics articles confirms that trade competition can have significant, negative impacts on employees with certain skill types, or those who are employed in exposed industries, such as durables manufacturing.

U.S. agriculture is an important counterexample, although it hasn't received a similar degree of attention: as we detail below, trade provides a substantial component of farm receipts every year. This Dissertation is structured to perform a set of analyses to measure the aggregated effects of trade on U.S. agriculture, from the exposure to China's demand for agricultural exports on U.S. county-level outcome variables, to the impact of import competition in the U.S. domestic agriculture industry from top international markets, and finally the aggregated impact of U.S. agricultural trade in general—exploiting the gains down on the farms from worldwide exports proportional to gains from China, in aggregation with loss stemming from international import competition, to discover the net benefit of what trade can offer for U.S. agriculture sector.

Background

Ever since David Ricardo introduced the theory of comparative advantage in the 19th century, as a discipline economics has maintained that international trade is beneficial (Krugman and Obstfeld, 2003) and can deliver net gains and raise living standards (Feenstra, 2018). Many of the models economists use demonstrate that trade is Pareto improving at the aggregate (national) level, meaning that at least one party wins without any other party losing. A large literature explores the benefits of free trade in terms of GDP growth, income growth, productivity increases, and even pollution reduction (Frankel and Romer, 1999; Antweiler et. al, 2001; Alcala and Ciccone, 2004).

U.S. policy towards international trade has evolved over time. At the end of the Second World War, average tariff rates in the United States were among the highest in the world, but for the past 70 years the United States has taken a prominent position in the establishment and preservation of the contemporary global framework for unrestricted commerce. It has actively worked towards diminishing global trade barriers through various means, such as engaging in both multilateral and bilateral trade agreements. Initially, this effort was conducted within the framework of the General Agreement on Tariffs and Trade (GATT), which eventually evolved into the World Trade Organization (WTO). (ERP, 2018). During this period, trade did not attract much negative attention, since much of it occurred among nations with comparable average incomes, limiting distributional impacts (Autor, 2018).

Rising adoption of communication and transportation innovations, like containerized shipping by developing countries from the late-1970s and onward (Levinson, 2006; Hummels, 2007), revolutionized international trade, affording consumers in rich nations the ability to access products of new factories located in cheaper labor markets. Shortly thereafter, from the early-1990s through the late-2000s the proportion of the working-age population engaged in the manufacturing sector experienced a significant decline, decreasing by one-third from 12.6 percent to 8.4 percent (Autor, Dorn, and Hanson, 2013). In contrast to the conventional understanding of U.S. labor markets as adaptable and dynamic, the decline in manufacturing jobs resulting from trade did not see compensatory effects through sectoral reassignment or labor mobility. (Autor, 2018), indicating long-term or even permanent impairment. China's accession to the WTO in 2001 invited an import surge that produced a literature (see, e.g., Autor et al. 2013, 2014, 2020; Acemoglu et al., 2016; and Pierce and Schott, 2016) studying its adverse employment and wage implications. Those authors estimate that the "China shock" reduced overall and manufacturing-sector U.S. employment by 2 million and 1.5 million jobs, respectively.

By the end of the 20th century, the American public and its politicians (see, e.g., Ross Perot's stance on the North American Free Trade Agreement) began a growing emphasis on the unequal distribution of trade benefits. (Kletzer, 2002). The U.S. public's enduring concerns over international trade are well summarized by a 2018 Harris Poll (2018) in which 71% of respondents indicate that the United States should "take steps to reduce the trade deficit with China, even if a resulting trade war drives up consumer prices". In 2018, the Trump Administration initiated a series of tariffs on washing machines, solar panels, steel, aluminum, and a range of Chinese products. In return, several major trading partners placed retaliatory tariffs on the United States (CRS, 2020a).

Although recent, high-profile academic work focuses on the workers, firms, and local communities that suffer dislocations from international competition, and some researchers have studied how the U.S. labor market adjusted to trade exposures (see, e.g., Acemoglu, 2003; Thoenig and Verdier, 2003; and Bloom et al., 2019), less attention is devoted to the gains that expanded market access offers domestic firms (in terms of export opportunities) and consumers (in terms of innovation, lower prices, and enhanced variety; see, e.g., Amiti et al., 2017; and Handley and Limao, 2017).

We target that gap, focusing on agriculture, an industry in which the United States holds a considerable comparative advantage owing to its geographical advantages, and effective integration of many strengths into the production process. The United States leads the world with $135.7 billion in agricultural exports and has been maintaining a trade surplus of $2.5 billion for agricultural goods in 2020. USDA forecasts that U.S. agricultural exports will continue to rise at an average annual rate of 2.2 percent per year for the rest of the decade. And between 2013 and 2017, agriculture ranked as the 4th highest domestic industry in U.S. exports, behind only transportation, electronics, and chemicals (USITC, 2018).

Structure

The dissertation is structured to perform a series of analyses that examine the aggregated net effects of trade on U.S. agriculture. Specifically, it consists of 3 individual Chapters.

In the first Chapter, we focus on what the United States is gaining in agricultural exports, where we use county-level data on agricultural outcomes and data on China’s imports of U.S. agricultural commodities to study the effect of growing 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. We find that the “China Shock” had a reverse effect on U.S. agriculture than it did on the manufacturing sector. We show that exposure to exports that China demands strongly and positively impacts U.S. county-level farm and employment outcomes. Exposure to exports that China demands strongly and positively impacts U.S. county-level soybean production, planting, and harvesting. Our results for other commodities highlight the intensity of the push to plant more soybeans to feed the Chinese swine herd. Higher county-level exposure led to higher farm income, accounting for 3% of average U.S. annual farm income, more acreage in production, less labor, and greater levels of farm value.

In the second Chapter, we look into what U.S. agriculture loses facing foreign import competition following similar trade exposure rate construction and IV strategy model from Chapter 1. We quantify how exposure to specific agricultural imports from the top 20 international suppliers in the world would affect the U.S. domestic county-level outcomes including the production, acreage, and price of certain imported products, farm income, and hired farm labor. We continue to adopt this county-specific agricultural import exposure metric, which signifies the portion of a county's agricultural yield contributing to the U.S. agricultural total imports for specific products. The metric is derived from (1) the nationwide percentage of the county's agricultural earnings in both livestock and crop sectors, and (2) the summation across these sectors to account for the county's agricultural import proportion to these countries. The methodology is modified to better suit the unique agricultural import structure. We adjust the composition of crop-related products to include only the products that are both imported and with massive domestic production, excluding all field crops. We also add a weight term to our model to balance the domestic production value generated between crop-related products and animal-related products. Additionally, we modify the instrumental variable technique to precisely identify the effects of unanticipated import supply shocks, thereby addressing the endogeneity challenge presented by unobserved domestic demand shocks. Specifically, we use data on U.S. agricultural imports from the rest of the World to instrument for changes in U.S. demand.

The constructed import exposure shows four times as large in magnitude compared with the export exposure to China, with less counties observed. Geological distribution is close to the export exposure map. Variation in different counties remain large. States with more fruit and vegetable production show improving exposure compared with traditional field crop production heavy states.

In our 2SLS estimation results, we find increasing import exposure result in increase in fruit sales but reduction in animal-related product sales. We find that import exposure strongly and negative impacts local farm-related employment and income, but the society's overall employment rate and income are positively connected with import exposure, indicating the existence of import competition. But the damage caused is likely absorbed by other industries and the aggregated influence from import exposure is beneficial.

After individually assessing gains from exports and losses from imports, Chapter 3 aggregates effects from both import and export sides to discover a net impact of trade on U.S. county-level outcomes. A major empirical challenge is the construction of net trade exposure. We follow Autor et al. (2013) and Choi and Lim (2022) to create our own net trade exposure model. Differed from the previous methodology utilized in Chapter 1 and 2, we difference the county-level proportioned contribution factor from exports and imports between any two discontinued time periods (not a continued time series) from 1997 to 2022, dividing by the county's population to construct a county-level aggregated trade exposure. We employ a different set of products at HS 6-digit level, constructing each product with its own import or export differences instead of aggregating to crop-related and animal-related products. We also explore deeper into the crosswalk between U.S. Ag Census data and the HS 6-digit level code to match each product individually.

Our core findings are as follows. The net trade exposure rates show less variation across U.S. counties compared with export and import exposures. And the trade war deeply challenged the net trade exposure rates. The net trade exposure largely benefits U.S. county-level aggregated net farm income and agricultural employment share of total working age population, across all 5-, 10-, and 15-year periods, contradictory to what has been discovered in the manufacturing industry. The change in net trade exposure during the trade war periods, which was directly affected by Trump administration's trade policies and its associated consequences, contribute to the achievement of their political targets and result in an increase in county-level voting shares in their favor.

CHAPTER 1

U.S. COUNTY-LEVEL IMPACTS OF CHINA'S DEMAND FOR AGRICULTURAL EXPORTS

Introduction

Since its accession to the World Trade Organization (WTO) in 2001, China's rapid expansion in global trade markets produced both winners and losers. Autor et al. (2013) demonstrate that rising exposure to the supply shock represented by imported manufacturing goods from China caused high unemployment, decrease in income and local labor employment participation in U.S. labor markets. A growing body of literature expands on that finding, exploring impacts on U.S. manufacturing employment and plants (Pierce and Schott, 2016), wage levels and public benefits (Autor et al., 2014), and U.S. manufacturing innovation (Bloom et al., 2015; Autor et al., 2020).

On the other hand, China's WTO accession opened a new market for U.S. agricultural exports. Figure 1.1 plots both the China-destined share of U.S. agricultural exports and the China-sourced share of total U.S. imports from 1990 to 2019. Notice their similar trends, both declined in 2017/2018 after fifteen years of increasing. From 1992 to 2007, U.S. agricultural exports to China increased from less than \$1 billion to more than \$20 billion, accounting for more than 40% of the U.S. total agricultural export growth. By 2017, China was the largest market for U.S.

agricultural exports. Although China's leading role in U.S. agricultural exports abruptly changed during the 2018 trade war,[1] it regained its leadership in 2020 and 2021.[2]

Compared with the manufacturing industry, U.S. agriculture is an important counterexample, although it hasn't received a similar degree of attention. To address this, following Autor et al. (2013), we quantify how exposure to China's demand for agricultural products affects a series of U.S. county-level outcomes including farm income, cropland acres, commodity prices, factor inputs, and other variables that represent general economic activity and well-being (including "misery" outcomes like obesity levels and premature death rates). Following Autor et al. (2013), we construct a county-level Chinese export exposure rate—that represents the contribution of the county's agricultural production to the share of U.S. agricultural sales for products demanded by China—based on (1) the national share of the county's agricultural income in both animal and crop categories, and (2) sum across both categories to account for the county's agricultural export amount share to China. We further adapt their instrumental variables strategy to properly identify the impact of unexpected export demand shocks, avoiding the problem of endogeneity posed by unobserved U.S.-specific productivity shocks that may drive changes in agricultural exports (using data from the ten other largest agricultural commodity exporters to China instrument for changes in Chinese demand).[3]

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[1] Began in 2018, China placed retaliatory tariffs on commodities that made up $20.6 billion of U.S. agricultural exports from the previous year, targeting all agricultural product categories. As a result, from 2017 to 2018, soybeans, cotton, and sorghum experienced total export value declines of 74.6%, 37.9% and 5.4% respectively, and China fell from the leading export market for U.S. agricultural products to third place, behind Canada and Mexico (CRS, 2018).

[2] Based on data from Global Agricultural Trade System (GATS) from USDA.

[3] To conduct the analysis, we link data from the U.S. Census of Agriculture, GATS (Global Agricultural Trade System), and UN Comtrade. As no such crosswalk between the ag census and ag trade data by commodity group previously existed, the concordance we built itself represents a contribution to researchers. See the data section for details.

To validate our model, we first examine how export exposure to China affects U.S. soybean acreage—expecting the relationship to be positive since China has half the world's pigs and is the prime export destination for the U.S. crop.[4] Unsurprisingly, we find a substantial impact: the average exposed county, a one-unit increase in export exposure raises a county's harvested soybean acres by over 407,000, its soybean production by 30.2 million bushels, and its soybean sales by nearly $300 million. The average exposure rise of 0.031 units implies an average county-level increase of over 12,600 harvested acres, 937,000 bushels, and almost $9.3 million in soybean sales. We also map our estimated change in county-level export exposure rate to China. States and counties with high soybean production and specialty crops show more increased exposure rates.

More generally, we find that higher exposure to Chinese export demand raises all-source county-level farm income, with each unit-level increase raising average county-level agricultural income by nearly $30.3 million. Given that there are 2732 observed counties in the data, we estimate the average export exposure to China raises real farm income to U.S. producers by $2.6 billion (in 2017 dollars), annually. We further find that higher export exposure to China increased total cropland acres, total harvested acres, the value of ag land and buildings in the United States and reduced hired farm labor. For "misery" variables, we find higher exposure to the China shock in ag-producing counties led to lower unemployment rates and premature death.

The rest of the Chapter is organized as follows. Section 2 reviews related background and literature. Section 3 describes the methodology. Section 4 provides data sources and descriptive analysis. Section 5 presents empirical results and Section 6 concludes the Chapter.

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[4] China is the home to over half of the world's pigs (FAS, 2019).

Background and Literature Review

Changing Perspectives on Trade of the United States and China

As trade theory initially being introduced, it was pictured as Pareto improving. A large body of literature explores the benefits of free trade in terms of GDP growth, income growth, productivity increases, and even pollution reduction (Frankel and Romer, 1999; Antweiler et al., 2001; Alcala and Ciccone, 2004). Over time, U.S. policy towards international trade has undergone a transformation, transitioning from a stance of trade protectionism before World War II to assuming a prominent position in the construction and maintenance of the contemporary global framework for unrestricted commerce. The United States has been actively involved in reducing global trade barriers through both multilateral and bilateral channels, initially operating within the framework of the General Agreement on Tariffs and Trade (GATT) and subsequently within the World Trade Organization (WTO) (ERP, 2018). During this period, trade did not attract much negative attention, since much of it occurred between nations with similar average incomes (Autor, 2018).

China, before its "Reform and Opening Up" policy in 1978,[5] was among the poorest countries in the world. Under the early communism economics structure, there were few foreign investments in China. International trade was only channeled through several state monopoly companies and seen as a method to acquire foreign assets to pay for imports oversea. It only contributed to less than 10 percent of China's GDP (DeLisle and Goldstein, 2019). During the 1990s, China initiated negotiations to enter the global market, and the United States played a significant role as a negotiating partner in this process. Following the establishment of a

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

memorandum of understanding on market access in 1992 between the United States and China, China implemented a series of agricultural tariff reductions and began aligning its trade classification system with the Harmonized System, a global framework of names and codes used for categorizing traded products. In 2001, with the effects of internal trade policy reforms, China gained its accession to the WTO and the most-favored-nation-status (Branstetter and Lardy, 2006).

Decline in U.S. Manufacturing Industry – The China Syndrome

Revolutionized international trade, owing largely to China's spectacular economic growth and its accession to the WTO in 2001, has enabled rich nations to access products from new factories located in much cheaper labor markets. As a result, from the early-1990s through the late 2000s, the fraction of working-age employment in U.S. manufacturing industry decreased from 12.6 percent to 8.4 percent (Autor et al., 2013). Trade-induced manufacturing job losses were not mitigated by labor reallocation or migration, contrary to the popular belief that the U.S. labor markets are fluid and flexible. The damage caused was likely to be long-term or even permanent (Autor, 2018). China's accession to the WTO in 2001 invited an import surge that produced a literature (see, e.g., Autor et al. 2013, 2014, 2020; Acemoglu et al., 2016; and Pierce and Schott, 2016) studying its adverse employment and wage implications. Those authors estimate that the "China shock" reduced overall and manufacturing-sector U.S. employment by 2 million and 1.5 million jobs, respectively.

Autor et al. (2013) conducted an analysis to examine the impact of increasing import competition from China on local labor markets in the United States during the period from 1990 to 2007. The study by Autor et al. (2013) reveals a distinct negative correlation between U.S. manufacturing employment and the level of import penetration from China.[6] In order to assess

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[6] Autor et al. (2013) define import penetration as U.S. imports from China divided by total U.S. expenditure on goods, measured across U.S. gross output plus U.S. imports minus U.S. exports.

the specific local impact of Chinese imports, Autor et al. (2013) employed the concept of commuting zones (CZs)[7] to localize the U.S. labor markets.

Autor et al. (2013) utilized an instrumental variable (IV) and a two-stage least squares (2SLS) approach to analyze the effects of increased Chinese imports in the manufacturing industry on U.S. local labor markets. By examining commuting zones (CZs) and accounting for geographical variations in the importance of different manufacturing sectors for local employment, they found that higher levels of import competition from China resulted in elevated unemployment rates, reduced wages, and lower labor force participation in these local labor markets.

This study sparked a series of subsequent research that employed similar exposure rate constructions and instrumental variable strategies to explore the relationship between local exposure to Chinese imports and various outcomes. These include investigations into housing prices and business activity (Feler and Senses, 2017), innovation levels of U.S. manufacturing firms (Zhang, 2017), impact on voters (Dipple et al., 2017), employment levels in other countries like Japan (Yamashita, 2017), and even the phenomenon of populist backlash (Barone and Kreuter, 2021).

U.S.-China Agricultural Trade and the Trade War

One industry that the United States has been holding a comparative advantage for a long time and requires attention is agriculture. Between 2013 and 2017, the agricultural industry was ranked 4th highest in U.S. exports by industry sectors on average, behind transportation, electronics, and chemicals (USITC, 2018). The United States leads the world in agricultural exports with $135.7 billion and runs a trade surplus of $2.5 billion for agricultural goods in 2020.

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[7] Commuting zones are geographic units that encompass all metropolitan and nonmetropolitan areas in the United States. They are intended for use as measures of local labor markets when researchers are not concerned with minimum population thresholds. (Tolbert and Sizer, 1996)

Meanwhile, China is the world's leading producer and consumer of various agricultural commodities. Since China joined the WTO in 2001, it has become one of the most active and involved countries in global agricultural markets, thanks to its improving economic power with higher domestic living standards and agricultural production, along with changing agricultural policy.

While imports from China surged in the U.S. manufacturing industry, the Agricultural sector is a perfect counterexample where China has been purchasing from the United States. Figure 1.2 plots the U.S. agricultural exports to China. From 2001 to 2020, U.S. agricultural exports to China have expanded more than 15 times from less than 2 billion dollars to 29.4 billion dollars (in 2020 real dollars). According to the Congressional Research Service (CRS, 2019), China held the position of the largest recipient of U.S. agricultural exports in terms of value from 2010 to 2016. Notable U.S. domestic export categories during this period included soybeans (amounting to $14 billion), pork and pork products ($2.3 billion), cotton ($1.8 billion), corn ($1.2 billion), and coarse grains (excluding corn) ($1.1 billion). Among all commodities, soybean is the largest exporting agricultural commodity in the United States and China has been the world's largest soybean importer. In 2020, soybean ranked second among all U.S. export categories (2-digit HS), only falling behind electrical machinery (USTR, 2020).

As the agricultural trade relationship between the United States and China develops over the last two decades, by the end of the 20th century, the American public and its politicians began to focus on the uneven distribution of the benefits from trade.[8] Starting from the manufacturing industry, the impact of trade on the United States gradually spread out. The U.S. public's

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[8] See, e.g., Ross Perot's stance on the North American Free Trade Agreement. Accessed at: https://www.nytimes.com/2019/07/09/business/economy/ross-perot-nafta-trade.html

enduring concerns over international trade are well summarized by a 2018 Harris Poll (2018) in which 71% of respondents indicate that the United States should "take steps to reduce the trade deficit with China, even if resulting trade war drives up consumer prices."

In 2018, the Trump Administration initiated a series of tariffs on washing machines, solar panels, steel, aluminum, and a range of Chinese products. In return, several U.S. major trading partners, led by China, placed retaliatory tariffs directed at $26.9 billion in 2017 U.S. agricultural exports on the United States, representing 18% of the value of U.S. agricultural and food exports globally (CRS, 2018; 2020b). Table 1.1 shows a brief timeline of U.S. tariff initiations and China's retaliatory tariffs.

As a result, U.S. agricultural exports to China declined 53% in value to $9 billion from 2017 to 2018. By mid-2019, China's market fell from top to the fourth-largest destination for U.S. agricultural exports. U.S. soybean products suffered the hardest hit. In 2018/19, U.S. soybean ending stocks reached over 900 million bushels, 60% higher than the previous historical record. The USDA initiated two rounds of trade aid package to U.S. farmers due to a fifth consecutive year of relatively low U.S. agricultural commodity prices, contributed by factors including low U.S. exports, abundant international supplies and the unresolved trade disputes (CRS, 2019). On Jan 15th, 2020, President Trump signed a phase one trade agreement with the Chinese government (CRS, 2020b). After the phase one deal, China regained its leading U.S. agricultural export destination position in 2020 and 2021.

Methodology

An Instrumental Variable and 2SLS Estimation Strategy from Autor et al. (2013)

We adapt this instrumental and 2SLS estimation strategy from Autor et al. (2013). Their main measure is to assign an exposure value to Chinese imports to each commuting zone using the change in Chinese imports per worker in the commuting zone, where imports are apportioned to the commuting zone according to its share of national industry employment.

$$\Delta \mathrm{IPW}_{\mathrm{uit}} = \Sigma_{\mathrm{j}} \frac{\mathrm{L}_{\mathrm{ijt}}}{\mathrm{L}_{\mathrm{ujt}}} \frac{\Delta \mathrm{M}_{\mathrm{ucjt}}}{\mathrm{L}_{\mathrm{it}}} \; (1.1)$$

In this expression, L_{it} is the beginning-of-period employment (year t) in commuting zone i and $\Delta\mathrm{M}_{\mathrm{ucjt}}$ is the observed change in U.S. imports from China in industry j between the start and the end of the period. $\frac{\mathrm{L}_{\mathrm{ijt}}}{\mathrm{L}_{\mathrm{ujt}}}$ is the national proportion of commuting zone i's industry j's employment (u represents the United States). The sum across different industries t yields the changed exposure rate (import per worker) for each commuting zone between time periods.

However, the major empirical challenge of this methodology in identifying the causal effect of Chinese imports is the unobservable U.S.-specific demand shocks. Realized U.S. imports from China in equation (1.1) may be correlated with industry import demand shocks, biasing the OLS estimates of the effects of increased imports from China on U.S. manufacturing employment. The core assumption is that China's internal supply shocks, stemming from its own economic development and failing trade costs, are the reason for the surge of Chinese imports, instead of U.S.-specific demand and productivity shocks. To deal with this endogeneity issue, Autor et al. (2013) use an instrumental strategy based on Chinese import growth in other high-income markets,[9] which also endured with the surge of Chinese imports but unrelated to U.S. local labor outcomes, making it a good instrument choice. The expression of the instrument variable is similar to the main exposure construction. Instead of the U.S., it uses the other eight high-income markets' imports from China. And the use of lagged employment levels mitigates the simultaneity bias that employment is contemporaneously adjusting to anticipated Chinese trade.

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[9] The high-income markets selected are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

$$\Delta \mathrm{IPW}_{\mathrm{oit}} = \Sigma_{\mathrm{j}} \frac{\mathrm{L}_{\mathrm{ijt-1}}}{\mathrm{L}_{\mathrm{ujt-1}}} \frac{\Delta \mathrm{M}_{\mathrm{ocjt}}}{\mathrm{L}_{\mathrm{it-1}}} \ (1.2)$$

Construction of U.S. County-Level Agricultural Export Exposure Rate to China's Demand

Based on the empirical framework developed by Autor et al. (2013), we construct a measure of exposure over time to Chinese exports as the source of local agricultural outcomes. We use county as our unit of analysis due to (1) the availability of data collected from the U.S. Agricultural Census, (2) the lack of natural aggregation in agricultural outcomes like the commuting zones. Also, instead of using regional employment figures, we use the market value of agricultural products sold from each county as a baseline input aggregated from crop-related value and animal-related value in place of different manufacturing industries. The market value of agricultural products sold is an ideal proxy to measure export exposure because it captures all agricultural commodities, not only field crops, but including animal-related poultry, dairy product value that cannot be simply measured by acreage, weight, or production due to the added value. In contrast to Autor et al. (2013)'s import per worker variable, we calculate export value per dollar (of agricultural products sold) on county-level. The change in exports per dollar is constructed as the expression below:

$$\Delta \mathrm{EPD}_{\mathrm{uit}} = \Sigma_{\mathrm{j}} \frac{\mathrm{W}_{\mathrm{ijt}}}{\mathrm{W}_{\mathrm{ujt}}} \frac{\Delta \mathrm{E}_{\mathrm{ucjt}}}{\mathrm{W}_{\mathrm{it}}} \ (1.3)$$

$\Delta \mathrm{EPD}_{\mathrm{uit}}$ is the change in the U.S. (u stands for the United States) agricultural export exposure in year t for county i. $\frac{\mathrm{W}_{\mathrm{ijt}}}{\mathrm{W}_{\mathrm{ujt}}}$ is the proportion of county i's agricultural commodity group j (either crop or animal)'s value sold in the whole United States at the start of year t. W_{it} is the beginning-of-period value of all agricultural commodities sold in year t county i, and $\Delta \mathrm{E}_{\mathrm{ucjt}}$ is the observed change in U.S. exports to China in group j between the start and the end of the period. This expression apportions the change in the value of U.S. exports to China in a specific commodity group depending on how this commodity group's market value sold is initially distributed across counties in the United States and then rescales this value by county's total market value of agricultural commodities sold. The resulting value of $\Delta \mathrm{EPD}_{\mathrm{uit}}$ is a unit-free ratio.

Endogeneity of Trade Shocks

Similar to the potential U.S. demand shocks posed in U.S. manufacturing imports in Autor et al. (2013), unobserved U.S. specific positive supply and productivity shocks may drive this surge in U.S. agricultural exports to China. This omitted U.S. specific shock could be correlated with our independent variable, the county-level exposure rates, thus causing bias in our estimations. Our target is to identify the assumption that China's internal demand shocks, for instance, its own economic growth with rising living standards, changing structure of food demands, short of land-intensive commodities compared with labor-intensive commodities, lead to this change in export exposure. To tackle this issue, we also adapt Autor et al. (2013)'s instrumental variables strategy to properly identify the impact of trade shocks, using data from 10 other largest agricultural exporters to China to construct an instrument for changes in Chinese demand.[10] The agricultural exports to China from other large exporters to China (IV) are intuitively correlated with U.S. exports exposure to China (independent variables). Also, they can only impact U.S. county-level outcomes (dependent variables) by affecting U.S. exports and they are not correlated with any omitted U.S. specific supply and productivity shocks, which makes them ideal for instruments. The instrument is calculated as follows (o stands for other 10 largest exporters):

$$\Delta \mathrm{EPD}_{\mathrm{oit}} = \Sigma_{\mathrm{j}} \frac{\mathrm{W}_{\mathrm{ijt-1}}}{\mathrm{W}_{\mathrm{ujt-1}}} \frac{\Delta \mathrm{E}_{\mathrm{ocjt}}}{\mathrm{W}_{\mathrm{it-1}}} \; (1.4)$$

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[10] The 10 other largest exporters are Argentina, Brazil, Canada, India, New Zealand, Thailand, Ukraine, Uruguay, and Vietnam.

This non-U.S. exposure to export to China differs from equation (1.3) in two aspects. First, in place of U.S. agricultural exports by commodity group ΔE_{ucjt}, it uses exports from other 10 largest exporters in the world to China ΔE_{ocjt}. Second, in place of the start-of-period market value of agricultural product sold, this expression uses market value from the prior time period (5-year in our estimation). We use this five-year-lagged market value sold because the contemporaneous market value of agricultural product sold might be affected by anticipated China trade. The use of lagged market value to apportion predicted export to China to other exporters will mitigate this bias.

2SLS Model

We use a two-stage least squared model (2SLS), with the first stage regression constructed as follows:

$$\Delta EPD_{uit} = \alpha_{it} + \beta \Delta EPD_{oit} + u_{it} \quad (1.5)$$

In the second stage, we estimate the effects of changes in exports to China per dollar on U.S. local agricultural outcomes and "misery" variables, as follows:

$$\Delta A_{it} = \beta_1 \Delta EPD_{uit} + X'_{it}\beta_2 + \varepsilon_{it} \quad (1.6)$$

In equation (1.6), ΔA_{it} is the change in local outcome variables including farm income, total cropland acres, commodity prices, factor inputs, and other variables that represent general economic activity and well-being (including "misery" outcomes like obesity levels and premature death rates). Each specification is estimated using two-stage least squares (2SLS) by instrumenting the change in U.S. exports per dollar in county i (ΔEPD_{uit}) with the change in other 10 countries' exports to China (ΔEPD_{oit}).

Data and Descriptive Analysis

Data Sources

Our econometric approach combines data from 4 sources. The U.S. Census of Agriculture provides information on U.S. farm-related county-level outcomes, including our main estimator for our independent variable (the exposure rates), the market value of agricultural products sold, and a series of dependent variables, including production/acreage/sales for various field crops, farm income, hired farm labor, cropland acres and value of agricultural land and buildings. The County Health Rankings and Roadmaps Database developed by the University of Wisconsin Population Health Institute provides "misery" U.S. county-level dependent variables on a yearly base including adult obesity rate, premature death rate, smoking rate, high school graduation and general unemployment rate. For trade data, the GATS (Global Agricultural Trade System) and UN Comtrade database provide agricultural export data from the Unites States and other countries.

We use data from each five-year interval U.S. Census of Agriculture from 1997 to 2017 from the Census Quick Stats Database. For the market value of agricultural products sold, we select the aggregated group of crop totals and animal totals with all commodities available at the county-level in the year of 1997, 2002, 2007, 2012 and 2017. Across all 50 States (including Alaska and Hawaii, Washington, D.C. excluded), there are 3,073 counties in the dataset. One challenge inside the census data is that in order to avoid disclosing the data of individual farmers, the cells denoted with a "D" in the dataset account for a piece of the dataset. To address this problem, we dropped those counties with disclosed values when calculating county-level exposure rates and yielded 2,761 counties with calculated exposure rates.

Other Major Agricultural Exporters to China

Autor et al. (2013) use data on imports from 10 non-U.S. high-income countries to construct their instrument for a Chinese supply shock to the United States. In our case, we construct the instrument for a Chinese demand shock using export data from 10 large (non-U.S.) agricultural exporters. Based on data from GATS and UN Comtrade databases, ranking from their aggregated agricultural exports to China between 1997 and 2017, the 10 countries we use to construct the instrument are Argentina, Australia, Brazil, Canada, India, New Zealand, Thailand, Ukraine, Uruguay and Vietnam.

Table 1.2 shows the comparison between the United States and these other 10 countries' trade of agricultural products with China, especially their exports to China. The first column of Table 1.2 shows the value of annual U.S. agricultural exports to China for the years of 1997, 2002, 2007, 2012, and 2017. The volume of U.S. agricultural imports from China was substantially smaller than the volume of exports throughout these years, and the growth of exports far outpaced the growth of imports. The primary change in U.S.-China trade during our sample period is clearly the dramatic—over 11 times larger—increase of U.S. exports. While at the same time, U.S. exports to the rest of the World only roughly doubled in 15 years. Table 1.2 also summarizes the agricultural trade flow from the ten countries mentioned above to and from China. Like the United States, these countries have an export-oriented relationship with China when it comes to agricultural products, and they also experienced a dramatic (over 14 times) increase of export to China, and a more modest growth of export to the rest of the world, confirming that it is reasonable to use their export patterns to construct an instrumental variable.

Crosswalk on Agricultural Commodities Between U.S. Census Data and Trade Data

The main challenge we face before the calculation of export exposure and its attendant effects is to link the U.S. Agricultural Census product value data to the export data from GATS and UN Comtrade. Because in the export exposure calculation, we obtain the market value sold for each agricultural commodity, then aggregate on the level of crop or animal totals based on Census grouping methods. But when it comes to extracting the according export data, the grouping method becomes different, and it is difficult to determine which commodities need to be included. Census data are organized into two major groups: crop totals and animal totals, with 14 and 8 sub-categories, respectively. In GATS, we select the FATUS (Foreign Agricultural Trade of the United States) commodity grouping method, which by definition is a standard USDA aggregation of several thousand Harmonized Tariff Schedule (HTS) codes into the 213 agricultural groups most used by the public (USDA, 2020a). And in UN Comtrade, the data is reported in HS codes. This is a challenging process because there is not existing crosswalk in commodity groups between either FATUS grouping or HS grouping export data and U.S. Agricultural Census domestic data, so are building a mapping concordance to match the data in terms of aggregated crop and animal totals from these three databases. See the Appendix A for the details.

County-Level Exposure Rates to Rising Chinese Demands

With all the data mentioned above available, we can calculate each county's exposure rates to growing Chinese demand for agricultural exports. For our main estimation, we use the growth between the year of 2007 and 2017. We selected this 10-year gap because our data limits as early as 1997. Since we use lagged terms in our instrumental variable calculation, we use 1997 to 2007 as the lagged previous decadal term. Table 1.3 shows descriptive statistics for our calculated county-level export exposure rate between 2007 and 2017 ($\Delta\mathrm{EPD}_{\mathrm{uit}}$ from equation

1.3). The average exposure rate is 0.0305. In the median county, the 10-year change in exports to China was 0.0298 from 2007 to 2017. The top counties' exposure rates are two times as large as the median county and the bottom county only has 25% of the median county's exposure. All observations have positive values indicating an increase in agricultural export exposure to China across all U.S. counties between 2007 and 2017.

Additionally, Figure 1.3 plots the variation in our constructed county-level exposure rate to export to China between 2007 and 2017. We can observe substantial variation in exposure rates across the country. Clearly, counties with heavy production of commodities including soybeans, wheat, cotton, and sorghum show higher exposure rates. In Corn Belts States (soybeans and corn), Southern States (cotton) and the States of Washington (wheat) and California (tree nuts and dairy products), exposures to China are expected to be higher than other locations in the United States due to local crop choices with high Chinese demand.

Results

First Stage of 2SLS

To analyze the efficiency of our instrumental variable, we run the first stage of the 2SLS regression. Table 1.4 presents the first stage regression results. The first stage results suggest there exists a consistent positive relationship between export exposure rates to China in the United States and the other 10 largest exporters to China. Figure 1.4 sketches the substantial predictive power. A single unit increase in instrumental export exposure rates to China from the other 10 largest exporters (lagged term) would increase the export exposure rates to China in the United States by 57.7 units. The R-squared number is 0.842 and F statistics easily exceed standard hurdles. It suggests the existence of a strong China shock.

Soybean and Other Major Agricultural Commodities

To validate our model, we first examine how export exposure to China affects U.S. soybean activities. Because China has half the global swine herd, its demand for herd feeding has become the prime driving force of soybean exports from the United States (Adjemian et al., 2021). Since China joined the WTO in 2001 until 2021, U.S soybean exports expanded over 5 times and export to China expanded more than 14 times. Between our estimation period 2007 to 2017, China accounts for more than 57% of U.S. soybean export. And the soybean export accounts for more than 58% of total U.S. agricultural exports to China. It is reasonable to describe soybean as the core of U.S. agricultural exports to China. Thus, we expect the relationship to be highly positive and significant between export exposure to China and U.S. soybean activities.

Unsurprisingly, we find a substantial impact. Table 1.5 presents the 2SLS regression results. The average exposed county, a one-unit increase in change in export exposure raises a county's increased harvested soybean acres by over 407,000, its increased soybean production by 30.2 million bushels, and its increased soybean sales by nearly $300 million. The average change in exposure rise of 0.031 units implies an average county-level increase of over 12,600 harvested acres, 937,000 bushels, and almost $9.3 million in soybean sales. The results suggest that export exposure to China affects deeply and positively in U.S. soybean industry on the farm level.

Because our model utilizes the exposure rate in the export difference between 2007 and 2017, it allows us to simulate the model-estimated changes in respective variables, by adjusting the terminal value of export in 2017, to compare with the realized data after 2017. Table 1.6 summarizes the model-estimated results with realized data from 2018 to 2020. In 2018, the model pessimistically predicts the change in soybean activities due to the dramatic decline in

U.S. export exposure to China caused by the trade war. The potential reason could be the delayed market reaction as the production of soybean did not decline in 2018 (4.41 billion bushels in 2017 and 4.43 billion bushels in 2018) whereas the export of soybeans to China declined dramatically (2.58 billion bushels in 2017 and 1.74 billion bushels in 2018). Because our model only captures the change in export exposure through export changes instead of production changes, a huge decline in export amount would cause the model to overpredict the loss. But in 2019 and 2020, our model makes fairly accurate predictions compared with the realized results, indicating overall good predictability of our model. The soybean sales increase in 2020 is underestimated caused by China's commitment to the Phase 1 deal which began making purchases in January 2020.

Additionally, we examine the export exposure impact on other major U.S. exporting agricultural commodities to China: cotton, wheat, and sorghum. Even though the value of export remains on high levels across 2007 to 2017, the impacts of exposure to China on other commodities are not as profound as it is in soybeans. Table 1.7 shows the 2SLS regression results between export exposure to China and other commodity activities. All three columns in cotton production, wheat and sorghum acres harvested show negative coefficients, indicating the counties that are more exposed to exports to China would have declines in these categories.

It is surprising to find a reverse effect from export exposure to China on other major exporting commodities. Changes in cotton production, wheat acres harvested, and sorghum acres harvested all see declines facing increased export exposure to China. Table 1.8 shows the model-estimated results compared with realized data. Again, the model performance hits its worst in 2018 with mostly correct signs of results in 2019 and 2020.

Noticeably, the results also suggest the existence of crop switching down at the county level. Out of the 390, 1692, and 435 counties that grow cotton, wheat, and sorghum in both 2007 and 2017, there 245, 1276, and 301 counties also grow soybeans in both years, accounting for 62.8%, 75.4%, and 69.2% respectively. It suggests that most counties that grow other types of major exporting commodities, also grow soybeans at the same time. Figure 1.5 pictures the acres harvested for these four types of major exporting commodities. We can observe that the total acres harvested do not change much over time due to the high utilization of farmland resources. But starting from 2007, the crop composition shifts from the other three commodities towards soybeans. Our regression results suggest that this export-oriented crop switching does exist, and China's growing demand is an important contributing factor. This finding aligns with USDA (2023a)'s summary that evolving U.S. agricultural policy has given farmers more flexibility in crop choices in response to market signals and that soybeans are the main contributing factor of U.S. total acreage planted since the 1990s. However, while crop-switching may occur in response to export demand, it's important to exercise caution when making definitive claims, as there exist numerous factors that influence crop choice, and the evidence down on the farm level could be inconclusive.

General Agricultural Outcomes

More generally, there are five different agriculture-related outcomes we study in this main estimation. Each column of Table 1.9 provides results from the estimation between the change in export exposure to China and one outcome. Our estimates show statistically significant and high-level effects of export growth to China on U.S. agricultural outcomes, over the period of 2007 and 2017. We find that growing export exposure to China led to significant increases in all-source U.S. farm income, both cropland acres and cropland harvested acres, the value of agricultural land and buildings, and decreases in hired farm labor.

Column (1) shows the results between export exposure to China and farm all-source county level U.S. farm income, with each unit-level increase raising average county-level agricultural income by nearly \$30.3 million. Given that there are 2732 observed counties in the data, we estimate the average increase in export exposure to China raises real farm income to U.S. producers by \$2.6 billion (in 2017 real dollars), annually, accounting for 3% of U.S. 10-year (2007-2017) average farm income at \$86.9 billion. What's worth mentioning is that because our estimation studies two discontinued time periods (not a continuous time series), the outcome levels at both the start of and the end of periods affect our estimation results. Figure 1.6 shows the U.S. farm-related income since 1997. It is clear that the U.S. farm income hit a trough (a 20% decline compared with peaks in 2012 and 2013) in 2017. Thus, the true impact of Chinese export exposure on farm income could be much larger.

Column (2) and (3) shows the results between the change in export exposure to China and both change in cropland acres and harvested cropland acres, with each unit-level increase raising average county-level cropland acres by 172.2 thousand acres and harvested cropland acres by 146.8 thousand acres. Annually, the average level of increase in exposure to exports to China for 2759 and 2714 observed counties generates 14.7 million acres increase in cropland acres and 12.4 million acres in increased harvested cropland acres, representing 3.7% and 3.9% of U.S. total in each category in 2017. These results align with our expectations because most major agricultural crops exported to China, including soybean, corn, wheat, and cotton, are highly farmland-consuming. Column (4) also shows a positive relationship between change in export exposure to China and the change in value of agricultural land and buildings. Given that there are 2760 observed counties in the data, we estimate the average change in export exposure to China raises real farm income to U.S. producers by $476.4 billion (in 2017 real dollars), annually. These results suggest that U.S. farmers on the county-level have been investing and expanding production and related farm assets, facing growing demand of exports from China. Column (5) suggests a decrease in hired farm labor. One unit level of increase in change in export exposure to China would decrease county-level hired farm labor by 3859 persons. This is a reasonable result due to the high level of U.S. farm machinery and automation, especially in export-oriented commodities.

Although the impact of export exposure to China is at a high level with statistical significance across all outcomes estimated, the R-squared numbers are small (less than 5%), meaning the effect scale on these general agricultural outcomes generated specifically from the China shock is smaller compared with its effect on soybean activities (from 7% to 15%), and much smaller compared with what happened in the manufacturing industry (more than 50% in Autor et al. (2013)). This could stem from (1) less-concentrated U.S. agricultural export destinations. China is one of the main targets of U.S. agricultural exports and remains on top for a long period. But the increase in U.S. agricultural exports was not completely driven by China. Countries including Canada, Mexico from NAFTA, and other Asia countries including Japan also contribute heavily to this increase over the last two decades. While in the manufacturing industry, it was almost the “Made in China” surge that single-handedly drove the rise in U.S. manufacturing imports with no similar level of competence, (2) the nature of geographical localization difference between commuting zones and counties. Commuting zones are highly concentrated and logical units for defining local labor markets for collecting employment data. Whereas counties are administrative geographical units that are highly disaggregated when it comes to agriculture-related outcomes. Adjacent counties could vary much in one outcome statistics with similar geographic backgrounds. Nevertheless, low R-squared numbers should not undermine the huge impact generated by growing Chinese demands for agricultural exports.

Table 1.10 provides a comparison between the model estimated changes and realized changes in farm income and hired farm labors. What's noticeable is that for realized datapost-20177, we use lagged by 1-year and 6-month data for farm income and hired farm labor, respectively. It's because the data was reported in the fiscal year in which USDA calculates each year's farm income from the previous year's October 1st to this year's September 30th. Thus, to capture the 2018 trade war effects, it is only ideal to consider farm income reported by USDA in 2019 to capture the reflected change starting from October 2018. A similar reason applies for hired farm labor. As we can see, the model predicts the farm income change accurately, except for a boost in farm income from late 2020 to 2021. The hired farm labor change is captured in 2019 and 2020 as well.

"Misery" Variables

Additionally, Table 1.11 presents some interesting results regarding the relationship between export exposure to China and some "misery" county-level variables that are not directly connected to agriculture. We find statistically significant results in outcomes including premature death rate, high school graduation rate and unemployment rate. Higher exposure to the China shock in ag-producing counties led to lower premature death rate, high school graduation rate and unemployment rate, with each unit-level increase decreasing average county-level premature death rate by 0.002 percentage points, high school graduation rate by 0.51 percentage points and unemployment rate by 0.229 percentage points. According to CDC, the top five premature death reasons are heart unintentional injury, respiratory disease, heart disease, stroke, and cancer, whereas unintentional injury ranks top in 2017. In more agricultural-related states, unintentional injury rates tend to be smaller than those in other states. Also, farmers represent a group that do not require strong educational backgrounds Thus, higher exposure to agricultural exports would indicate lower overall high school graduation rates. Also, despite we find higher exposure leads to lower hired farm labor, the overall county-level unemployment rates decrease.

Conclusions

Despite recent trade conflicts and the damage caused in U.S. agricultural sector, the United States and China have been each other's largest trade partners for years and likely will be for years to come. The United States has been largely importing manufactured goods from China, and these imports have affected U.S. manufacturing employment and other outcomes. A highly prominent research paper authored by Autor et al. (2013) develops an applied instrumental variable methodology and estimates large and negative effects of growing U.S. imports from China on U.S. manufacturing employment and on other outcomes. While this paper has been extremely influential in helping understand the consequences of growing U.S. trade with China, it only provides a slice of the overall picture. The estimates and many follow-up researchers only consider manufacturing trade and look only at the effect of U.S. imports from China.

Our research follows Autor et al. (2013)'s methodology and examines the U.S. county-level impact of China's demand for agricultural exports. Our findings quantify China's impact on U.S. agricultural exports and target the literature gap regarding the beneficial side of the "China Shock" generated in the agricultural sector.

We find that the "China Shock", on a smaller scale, had a reverse effect on U.S. agriculture than it did on the manufacturing sector. States and counties vary in exposure rates depending on whether their crop choices are export-oriented. We find that the change in exposure to agricultural exports that China demands strongly and positively impacts U.S. county-level soybean production, planting, and harvesting. Our result for other commodities highlights the intensity of the push to plant more soybeans to feed the Chinese swine herd.

Also, we find that higher county-level exposure led to higher farm income, with an estimation of a $2.6 billion increase annually that accounts for 3% of the U.S. average farm income between 2007 and 2017. Higher exposure also leads to more acreage in production, less labor, and greater levels of farm value. In “misery” variables, higher exposure to the China shock in ag-producing counties also led to lower unemployment rates and premature death rates, and high school graduation rates.

Table 1.1. Timeline of U.S. Tariff Initiations and China's Retaliatory Tariffs[11]

U.S. Tariff Initiation Area	Date	Total Value Impacted	China's Retaliatory Tariff Area	Date	Total Value Impacted
Solar Panel and Washing Machine	1/22/2018	$10.3 billion	Sorghum	4/17/2018	$1 billion
Steel and Aluminum	3/1/2018	$48 billion	Aluminum waste and scrap, pork, fruits and nuts, etc	4/2/2018	$2.4 billion
1,333 Chinese Products with top sectors including machinery, mechanical appliances, and electrical equipment	4/3/2018-8/23/2018	$50 billion	U.S. transportation (vehicles, aircraft, and vessels) and vegetable products (largely soybeans)	4/4/2018-8/23/2018	$50 billion
$200 billion of imports from China with 50% of Intermediate Goods including computer and auto parts, 24% of consumer goods	9/24/2018	$200 billion	Intermediate Inputs and Capital Equipment	9/24/2018	$60 billion
Same $200 billion of imports but with increased tariff rate from 10% to 25%	5/10/2019	$200 billion	Similar Tariff Hike in Return	6/1/2019	$36 billion out of $60 billion

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[11] Source: Bown and Kolb (2023). "Trump's Trade War Timeline: An Up-to-Date Guide". Peterson Institute for International Economics.

Table 1.2. The United States and 10 Other Largest Exporters' Value of Trade of Agricultural Products with China, 1997-2017, in 2017 Real Million Dollars[12]

	Trade with China		Trade with Rest of World
	Exports to China	Imports from China	Exports to Rest of World
United States			
1997	1,604.1	0.7	61,245.6
2002	2,065.3	1.1	53,711.5
2007	8,364.2	3.0	84,735.1
2012	25,885.0	4.5	120,032.8
2017	19,557.8	4.5	123,308.1
Growth 1997-2017	1119%	535%	101%
Other 10 Countries			
1997	3,781.9	476.7	81,681.9
2002	4,767.7	850.9	88,761.5
2007	17,509.3	2.277.1	174,481.1
2012	51,133.6	5,916.2	278,813.7
2017	58,595.4	9,468.5	255,082.1
Growth 1997-2017	1449%	1886%	212%

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[12] Source: Global Agricultural Trade System (GATS) from USDA and UN Comtrade Database

Table 1.3. Descriptive Statistics for Calculated Change of Agricultural Export Exposure Rates to China, 2007-2017[13]

Panel A. Percentiles				
90th Percentiles	75th Percentiles	50th Percentiles	25th Percentiles	10th Percentiles
0.0534	0.0438	0.0298	0.0166	0.0097
Average				
0.0305				
Panel B. Largest and Smallest Values among All Counties				
Top 5				
New Madrid, MO	Tensas, LA	Lake, TN	Philips, AR	Arkansas, AR
0.0600	0.0600	0.0600	0.0599	0.0599
Median				
Red River, LA				
0.0298				
Bottom 5				
Cleveland, AR	Banks, GA	Sabine, LA	Stephens, GA	Sevier, AR
0.0051	0.0051	0.0052	0.0053	0.0053

Table 1.4. First Stage Regression Results of 2SLS, Full Sample

	$\Delta \mathrm{EPD}_{u0717}$ (1)
$\Delta \mathrm{EPD}_{o9707}$	57.7***
	(0.5)
N	2761
R square	0.842
F-Stat	14655.9***

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

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[13] Table 1.3 reports 10-year values of exposure rates in aggregated market value of agricultural commodity sold per dollar of export to China, which is a unit-free ratio.

Table 1.5. Exports to China and Change of Soybean Activities in U.S. Counties, 2007-2017: 2SLS Estimates

	ΔSoybean Acres Harvested (1)	ΔSoybean Production in Bushels (2)	ΔSoybean Sales in 2017 Real Dollar (3)
$\Delta\mathrm{EPD}_{u0717}$	407,519*** (44,316.1)	30,233,837*** (2,154,518.0)	299,418,826*** (21,786,340.0)
N	1607	1598	1471
R-squared	0.072	0.140	0.153

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

Table 1.6. Comparison between Model Estimated Changes in Soybean Activities and Realized Changes[14]

	ΔSoybeans Acres Harvested in Million Acres		ΔSoybean Production in Bushels in Billion Bushels		ΔSoybean Sales in 2017 Real Dollar in Billion Dollars	
Year	Estimated	Realized	Estimated	Realized	Estimated	Realized
2018	-21.35	-1.95	-1.58	+0.02	-14.36	-4.49
2019	-12.90	-12.66	-0.95	-0.87	-8.68	-6.29
2020	+10.28	+7.94	+0.76	+0.58	+6.91	+15.21

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[14] Source: USDA (2020c; 2021)

Table 1.7. Exports to China and Change of Other Agricultural Commodities in U.S. Counties, 2007-2017: 2SLS Estimates

	ΔCotton Production in Bales (1)	ΔWheat Acres Harvested (2)	ΔSorghum Acres Harvested (3)
ΔEPD_{u0717}	-468,372*** (121,273.7)	-59,425* (30,939.9)	-235,636*** (45,294.8)
N	390	1692	435
R-squared	0.046	0.010	0.032

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

Table 1.8. Comparison between Model Estimated Changes in Other Agricultural Commodities in U.S. Counties and Realized Changes[15]

	ΔCotton Production in Million Bales		ΔWheat Acres Harvested in Million Acres		ΔSorghum Acres Harvested in Million Acres	
Year	Estimated	Realized	Estimated	Realized	Estimated	Realized
2018	+5.95	-2.56	+3.28	+2.06	+3.34	-0.02
2019	+3.60	+1.74	+1.98	-2.22	+2.02	+0.08
2020	-2.87	-4.96	-1.58	-0.65	-1.61	-0.10

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[15] Source: USDA (2020c; 2021)

Table 1.9. Exports to China and Change of General Agricultural Outcomes in U.S. Counties, 2007-2017: 2SLS Estimates

	ΔFarm Income in 2017 Real Dollar (1)	ΔCropland Acres (2)	ΔCropland Harvested Acres (3)	ΔValue of Ag Land and Buildings in 2017 Real Dollar (4)	ΔHired Farm Labor (5)
$\Delta \mathrm{EPD}_{u0717}$	30,273,993*** (4,720,587)	172,193*** (30,419)	146,809*** (30,270)	5,568,023,456*** (551,710,203)	-3,859*** (762)
N	2732	2759	2714	2760	1598
R-squared	0.025	0.015	0.006	0.047	0.004

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

Table 1.10. Comparison between Model Estimated Changes in General Agricultural Outcomes in U.S. Counties and Realized Changes[16]

	ΔFarm Income in 2017 real dollar in Billion Dollars		ΔHired Farm Labor In Million Workers	
Year	Estimated	Realized Lagged by 1-Year	Estimated	Realized Lagged by 6-Months
2018	-2.70	-3.90	+0.20	-0.15
2019	-1.63	-3.80	+0.12	+0.11
2020	+1.30	+73.30	-0.01	-0.21

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[16] Source: Post-2017 Farm income, hired farm labor data from USDA Farm Economy Databases. Other three variables not reported due to data limitations.

Table 1.11. Exports to China and Change of “Misery” Variables in U.S. Counties, 2007-2017: 2SLS Estimates

	ΔAdult Obesity Rate (1)	ΔPremature Death Rate (2)	ΔAdult Smoking Rate (3)	ΔHigh School Graduation Rate (4)	ΔUnemployment Rate (5)
$\Delta \mathrm{EPD}_{u0717}$	-0.036	-0.002**	0.077	-0.510**	-0.229***
	(0.049)	(0.001)	(0.099)	(0.226)	(0.051)
N	2719	2648	2156	2313	2719
R square	0.001	0.004	0.001	0.005	0.027

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

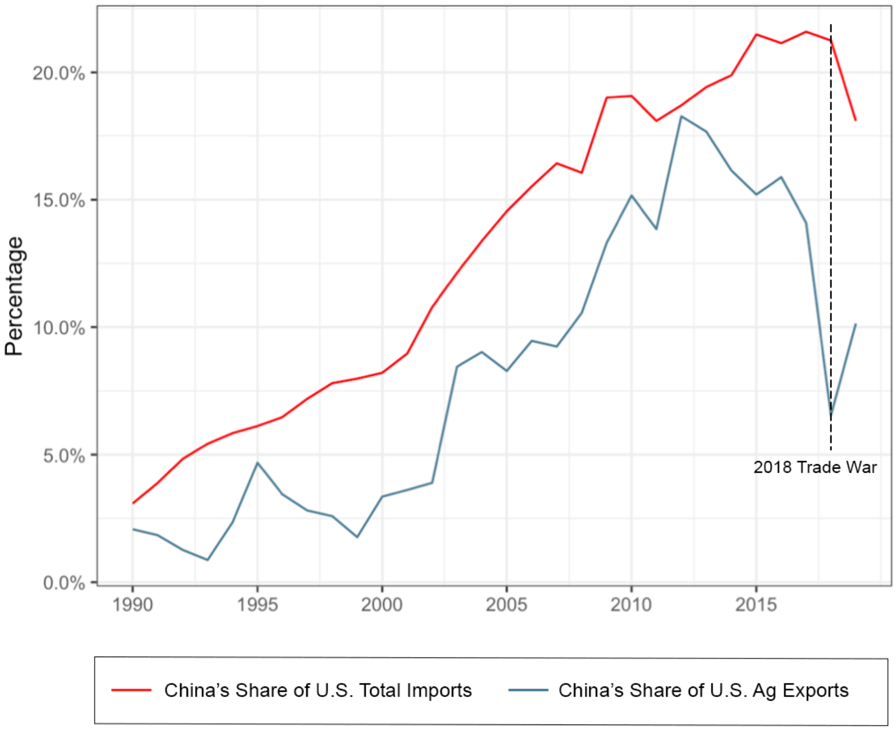

Figure 1.1. China's Share of U.S. Total Imports and U.S. Agricultural Exports, 1990-2019[17]

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[17] Source: Global Agricultural Trade System (GATS) from USDA and U.S. Census Bureau International Trade database.

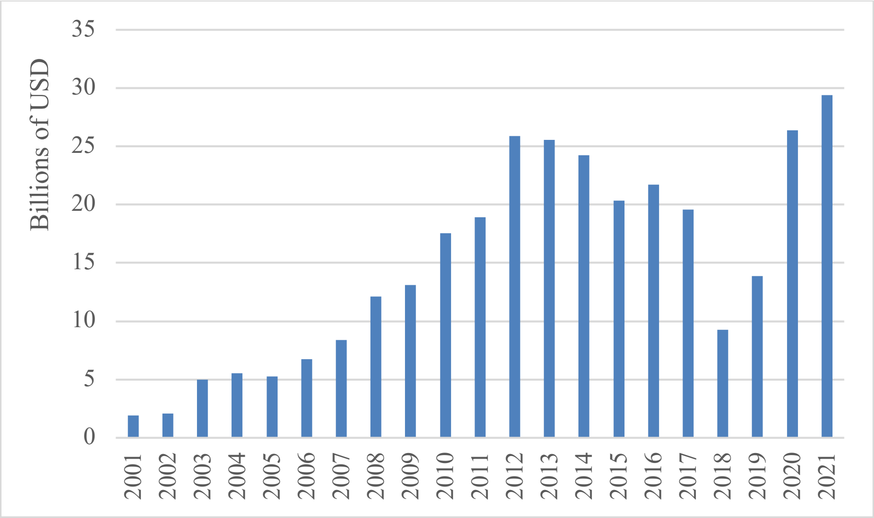

Figure 1.2. U.S. Agricultural Exports to China, 2001-2021, in 2020 Real Dollars[18]

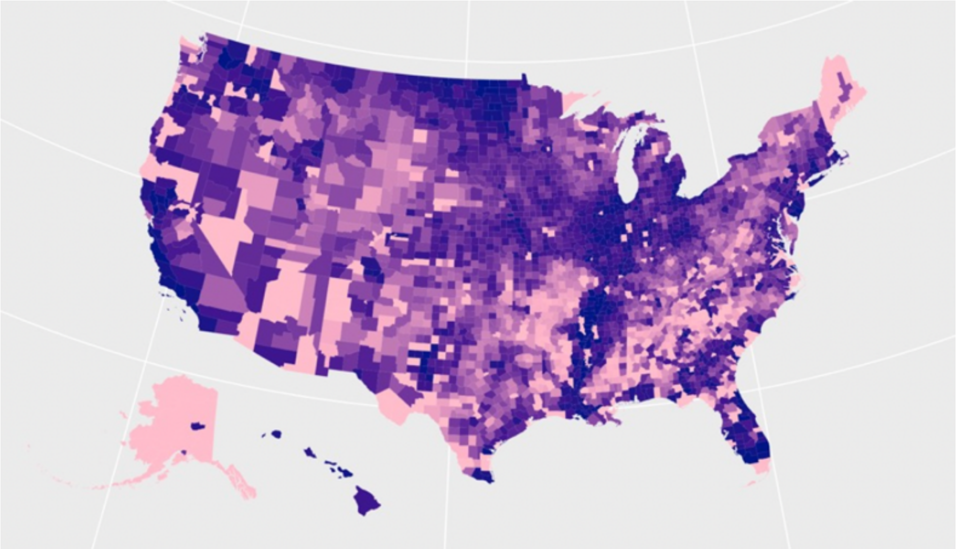

Figure 1.3. U.S. County-Level Export Exposure Rates to China[19]

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[18] Source: Global Agricultural Trade System (GATS) from USDA

[19] Darker colors represent greater levels of exposure.

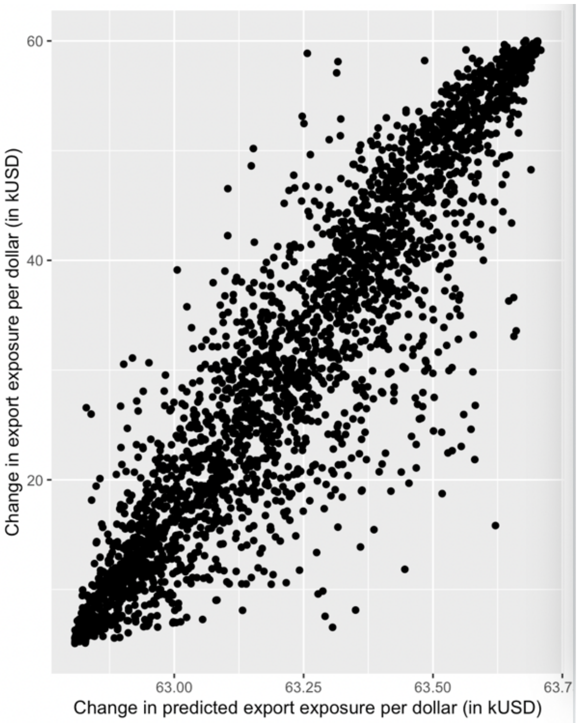

Figure 1.4. First Stage Regression Results of 2SLS, Full Sample

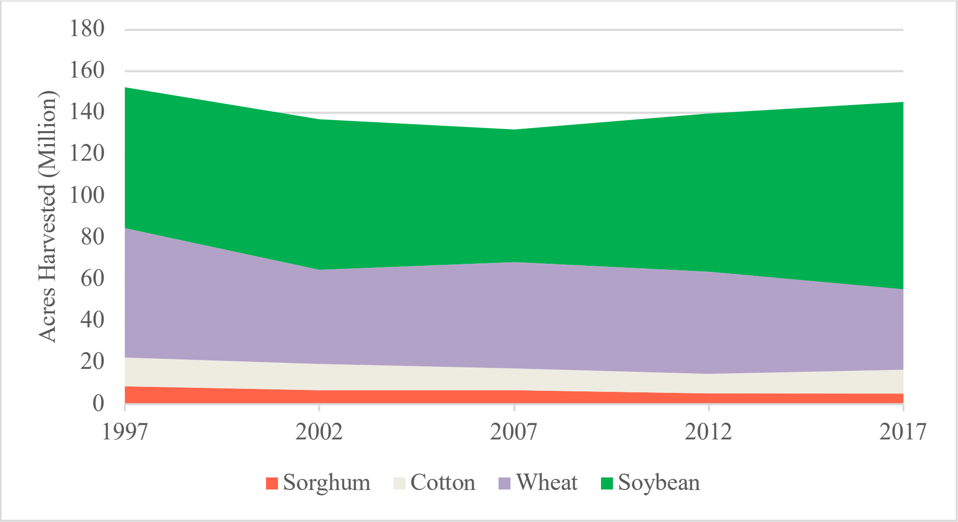

Figure 1.5. Select U.S. Crops Acres Harvested, 1997-2017[20]

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[20] Source: U.S. Census of Agriculture, QuickStats.

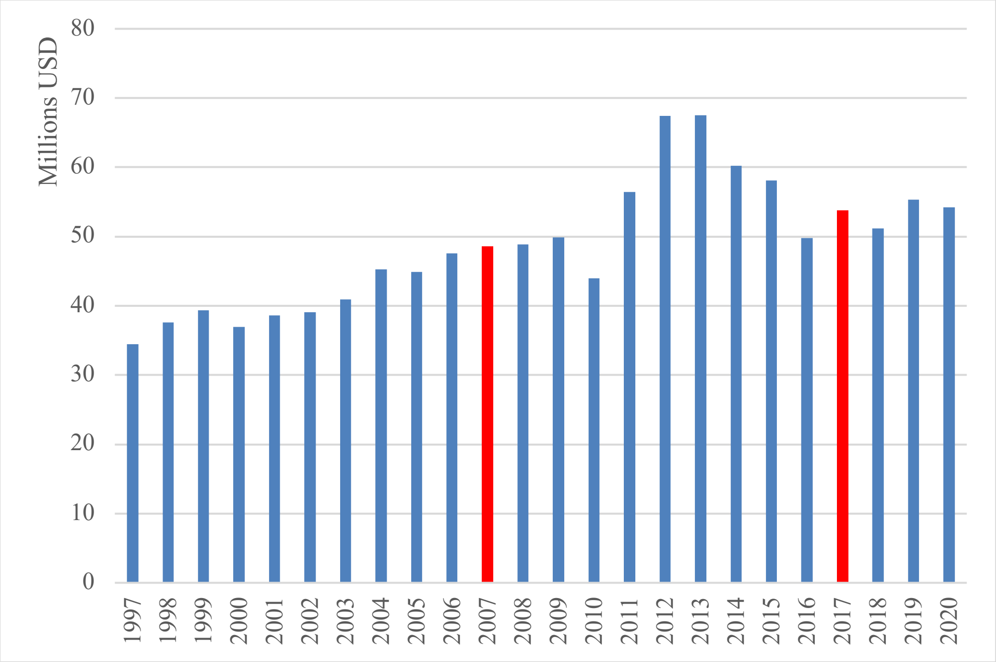

Figure 1.6. U.S. Farm Related Income, 1997-2020, in 2017 Real Dollars[21]

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[21] Source: U.S. Census of Agriculture, QuickStats.

CHAPTER 2

U.S. COUNTY-LEVEL IMPACTS OF AGRICULTURAL IMPORTS – AN ANALYSIS OF THE TOP INTERNATIONAL SUPPLIERS

Introduction

As the largest economy and one of the wealthiest countries in the World, the United States has been the world's largest agricultural importer, only recently surpassed by China in 2019 (USDA, 2020b). An ethnically diversified diet generated from high living standards, and comparative disadvantage in labor costs, combined with environmental and geological constraints, all contribute to the fact that the United States has a huge demand for agricultural imports.

In fact, even though the United States has been maintaining a trade surplus in the agriculture sector for more than 5 decades now, the gap has been closing between agricultural exports and imports. In 2019, for the first time since 1959, U.S. agricultural imports outnumbered exports (Snell, 2020). Although many would argue that this deficit was primarily driven by exports decreasing stemmed from the trade war, it was in fact, primarily due to escalating agricultural imports. Figure 2.1 plots U.S. agricultural imports, exports, and trade balance from 1967 to 2021. Notice that exports, despite the significant increase since the 1960s, have been relatively steady at around \$140 billion since 2011. However, the trade balance has been continuously decreasing since 2011, caused by the non-stop increase in imports. In fact, U.S. agricultural imports have increased annually every year since 1991, except only for the recession in 2009.

Unlike agricultural exports, imports are often overlooked when scholars study U.S. agricultural trade. In the manufacturing industry, massive and dramatically increased imports have led to severe consequences here in the United States (Autor et al., 2013). Competitions brought by imports from developing countries led to higher unemployment rates, lower salaries, and minimal transfer payments. Meanwhile, mounting agricultural imports receive far less attention compared with the manufacturing industry. Calculated based on the aggregated agricultural import value in 2017, more than 50% of the categories imported have U.S. domestic production. These imports can bring competition in aspects of price, market share, resource allocation, and shifts in consumer preferences. While it is unwise to easily undermine the benefits of imports, the lack of literature and econometrical tools for an import competition evaluation is also a contributing factor as to answer the question that whether agriculture suffers from imports like manufacturing does.

To view the whole picture of the U.S. agricultural trade, import is an essential part. Similar to the first Chapter, following Autor et al. (2013), we quantify how exposure to specific agricultural imports from the top 20 international suppliers in the world would affect the U.S. domestic county-level outcomes including the production, acreage, and price of certain imported products, farm income, and hired farm labor. We continue to adopt this county-specific agricultural import exposure metric, which signifies the portion of a county's agricultural yield contributing to the U.S. agricultural total imports for specific products. The metric is derived from (1) the nationwide percentage of the county's agricultural earnings in both livestock and crop sectors, and (2) the summation across these sectors to account for the county's agricultural import proportion to these countries. The methodology is modified to better suit the unique agricultural import structure. We adjust the composition of crop-related products to include only the products that are both imported and with massive domestic production, excluding all field crops. We also add a weight term to our model to balance the domestic production value generated between crop-related products and animal-related products.

Additionally, we modify the instrumental variable technique to precisely identify the effects of unanticipated import supply shocks, thereby addressing the endogeneity challenge presented by unobserved domestic demand shocks. Specifically, we use data on U.S. agricultural imports from the rest of the World to instrument for changes in U.S. demand.

The constructed import exposure shows four times as large in magnitude compared with the export exposure to China, with less counties observed. Geological distribution is close to the export exposure map. Variation in different counties remain large. States with more fruit and vegetable production show improving exposure compared with traditional field crop production heavy states.

In our 2SLS estimation results, we find increasing import exposure result in increase in fruit sales but reduction in animal-related product sales. We find that import exposure strongly and negative impacts local farm-related employment and income, but the society's overall employment rate and income are positively connected with import exposure, indicating the existence of import competition. But the damage caused is likely absorbed by other industries and the aggregated influence from import exposure is beneficial.

The rest of the Chapter is organized as follows. Section 2 reviews related background and literature. Section 3 describes the methodology. Section 4 provides data sources and descriptive analysis. Section 5 presents empirical results and Section 6 concludes the paper.

Background and Literature Review

History of Evolving U.S. Agricultural Imports

The history of U.S. agricultural trade is long and eventful, which can be traced back to the early colonial period when Europe is the primary destination of U.S. agricultural exports (Baldwin and Magee, 2000). However, the role of the United States in international agricultural trade has evolved over time, from being a predominantly export-oriented economy to one that also makes a significant volume of agricultural imports (Orden, 2013). U.S. domestic trade policies have evolved significantly in history to ensure the prosperity of agricultural imports. The 1930s marked the beginning of U.S. agricultural liberalization. The establishment of the Reciprocal Trade Agreements Act of 1934 served as a foundation for subsequent trade negotiations. In 1947, the General Agreement on Tariffs and Trade (GATT) further completed the liberalization of agricultural trade, leading to reduced trade barriers and increased imports (Anderson, 2014).

With the support of U.S. domestic policies, many factors start to contribute to the increasing agricultural imports. Bilateral and multilateral trade frameworks including the North American Free Trade Agreement (NAFTA) and the World Trade Organization (WTO) significantly impacted U.S. agricultural imports (Zahniser et al., 2015). Technology innovations, especially in transportation, storage, and communication, also boosted agricultural imports, including the development of the railroad and airfreight system for transport, refrigeration, and packaging technologies for perishable products (O'Rourke and Williamson, 2001), and the advent of the internet and digital communications for real-time information exchange.

Among all contributing factors, the most important one for the growth of agricultural imports is the dominantly leading economic position of the United States. The United States has been the World leader in terms of Gross Domestic Product (GDP) since the 1920s and it has consistently ranked among the World's highest in income per capita. High domestic living standards along with a growing population dramatically reshaped consumer preferences for diverse and high-quality products. As a result, the overall trend for U.S. agricultural imports has been upward since the latter half of the 20th century.

What and Where

U.S. agricultural imports consist of a diverse array of products. The Foreign Agricultural Service (FAS) of USDA defines its own product groups using the Harmonized Tariff Schedule (HTS) and titles these groups as BICO (HS-10) on a 10-digit level. BICO has three different groups that cover all U.S. agricultural trade-related products. The three groups are bulk, intermediate, and consumer-oriented. Table 2.1 lists some major products within each group.

Bulk commodities include products such as grains, oilseeds, and raw materials, which are typically traded in large volumes and have relatively low per-unit values. Meanwhile, high-value products include processed foods, beverages, and horticulture products, which are characterized by their higher per-unit values and smaller trade volumes (Zahniser et al., 2015). Figure 2.2 shows the composition of U.S. agricultural imports from 1967 to 2022. Consumer-oriented products dominate the imported products category, taking up around 70% of total U.S. agricultural imports, and have grown the fastest among all groups.

A series of literature (Dohlman and Gehlhar, 2007; Huang, 2013; Arnade and Kuchler, 2015; Orden, 2016) studies the reasons for this consumer-oriented import product domination. In this paper, we summarize them into two major perspectives. The first perspective is “to import the unavailable”, which includes reasons like diversified consumer preferences, year-round availability, and value-added products. Similar to what’s driving the U.S. agricultural import in general, with a diversified population that comes with varying tastes, preferences, and dietary requirements, there always exists a growing demand for a wide variety of food products from different regions and cultures, which U.S. domestic production may not always be able to fulfill. Products like fresh vegetables and fruits that do not have a year-long availability domestically are more favorable to be imported. Also, driven by factors such as urbanization, busy lifestyles, and craving for convenience, the demand for processed and ready-to-eat food products is also high. The second perspective is "available but better imported" and it is often overlooked by researchers. Not all U.S. agricultural imported products are only available overseas. In fact, based on our calculations from aggregated U.S. agricultural imports in 2017, more than 50% of the agricultural-related products imported are available within the United States or have domestic production. However, due to reasons of the cheaper price, better quality, and consumer preferences, the United States keeps mounting on importing these products.

In terms of the origins of U.S. agricultural imports, between the period of 2007 and 2017, the top 20 international suppliers together cover 80% of total U.S. agricultural imports. These top 20 countries are (in import value order high to low): Canada, Mexico, China, Brazil, France, Italy, India, Australia, New Zealand, Netherlands, United Kingdom, Germany, Spain, Chile, Colombia, Ireland, Guatemala, Thailand, Indonesia, and Vietnam. Figure 2.3 shows a pie chart of the originating regions of these top 20 countries. It is clear that the U.S. agricultural imports are from a diverse range of countries. North America, being Canada and Mexico, together consist of almost 40% of total U.S. agricultural imports, given the proximity and trade agreements in place. The European Union and Asia also have considerable shares.

Domestic Concerns Raised by Imports

As previously discussed, imported agricultural products can typically be grouped into two categories: (1) "to import the unavailable" and (2) "available but better imported". The second category, which has often been overlooked, presents potential for domestic competition. In the U.S. manufacturing industry, as discussed in the first Chapter, massive import competition from developing countries reshaped the whole industry. It sparks a series of literature assessing the damage caused from many different perspectives (see, e.g., Autor et al. 2013, 2014, 2020;

Acemoglu et al., 2016; and Pierce and Schott, 2016). However, little literature contributes to the fact that in agriculture, facing growing imports, domestic products are forced to deal with products from other countries that have lower production costs and more favorable growing conditions. This competition could result in reduced market share and lower revenues, leading to the need of cutting costs, labor reduction, and other unfavorable adjustments. The labor market is a significant area where vulnerable rural area agricultural workers could suffer decreased job security. Moreover, the pressure to remain competitive may drive domestic producers to put pressure on wages for those still employed in the sector, exacerbating income inequality, and potentially contributing to higher poverty rates. Bovay (2022) also discussed the concerns in food safety. Since the United States imports a wide range of products from all over the World, certain products may not meet the same rigorous safety standards applied domestically. In general, the continuous growth of U.S. agricultural imports raises certain concerns and to find whether similar damage exists in agriculture compared with manufacturing would contribute to this literature gap.

Methodology

Modified County-Level Import Exposure Rate Construction

We adopt this similar instrumental and 2SLS estimation strategy from Autor et al. (2013) that we utilize in our first Chapter, which was proven quite effective judging from the comparison between the model estimated effects and the realized effects post-2017 (see Table 1.6, 1.8 and 1.10 in Chapter 1). Based on the empirical framework developed by Autor et al. (2013), we construct a measure of exposure over time to U.S. agricultural imports as the source of local agricultural outcomes.

We keep using the market value of agricultural products sold from each county as a baseline input aggregated from crop-related value and animal-related value in place of different manufacturing industries. The market value of agricultural products sold is an ideal proxy to measure export exposure because it captures all agricultural commodities produced in the United States, not only field crops, but including animal-related poultry, and dairy product value that cannot be simply measured by acreage, weight, or production due to the added value.

In comparison to the model presented in Chapter 1, we introduce two key modifications to the model in Chapter 2. Firstly, we narrow down the range of domestic products analyzed in the model. While Chapter 1 focuses on a wide array of products exported from the United States to China, covering nearly all types of domestic production, Chapter 2 excludes products without import competition (e.g., field crops) and emphasizes a more selective set of domestically produced goods. Although we continue to categorize all domestically reported products (from the Census) into two primary categories – crop and animal -- we refine the inclusion criteria to four major categories: Grains, Vegetables, Fruits, and Horticulture Products to highlight products that encounter import competition. Animal-related products are still fully included.

Secondly, a consequence of these adjustments in product composition change is an increase in the proportion of animal product value sold compared with the four crop categories combined. However, when examining the U.S. agricultural imports, the imported value of these four crop categories is approximately double the value of animal-related products imported. To address this imbalance, we incorporate weighted terms in our model with a 66.7% weight to the crop category and a 33.3% weight to the animal category. This approach mitigates the disparities in domestic production.

In contrast to Autor et al. (2013)'s import per worker variable, we calculate import value per dollar (of agricultural products sold) on the county-level. The change in exports per dollar is constructed as the expression below:

$$\Delta \mathrm{IPD}_{\mathrm{uit}} = \Sigma_{\mathrm{j}} \frac{\mathrm{W}_{\mathrm{ijt}} \mathrm{P}_{\mathrm{j}}}{\mathrm{W}_{\mathrm{ujt}}} \frac{\Delta \mathrm{I}_{\mathrm{ucjt}}}{\mathrm{W}_{\mathrm{it}}} \quad (2.1)$$

$\Delta \mathrm{IPD}_{\mathrm{uit}}$ is the change in the U.S. (u stands for the United States) agricultural import exposure in year t for county i. $\frac{\mathrm{W}_{\mathrm{ijt}}}{\mathrm{W}_{\mathrm{ujt}}}$ is the proportion of county i's agricultural commodity group j (either crop or animal)'s value sold in the whole United States at the start of year t. P_{j} is the weight assigned to animal and crop category. W_{it} is the beginning-of-period value of all agricultural commodities sold in year t county i, and $\Delta \mathrm{I}_{\mathrm{ucjt}}$ is the observed change in U.S. imports from the top 20 international suppliers in group j between the start and the end of the period. This expression apportions the change in the value of U.S. imports in a specific commodity group depending on how this commodity group's market value sold is initially distributed across counties in the United States and then rescales this value by county's total market value of agricultural commodities sold. The resulting value of $\Delta \mathrm{IPD}_{\mathrm{uit}}$ is a unit-free ratio.

Similar Instrumental Variable Construction

Similar to the potential U.S. demand shocks posed by U.S. manufacturing imports in Autor et al. (2013), we monitor the source of this continuous growth in agricultural imports. Theoretically, both the U.S.-specific demand shock and the international countries' supply shock could contribute to this import surge. In contrast to Autor et al. (2013), which attributes the U.S. import boom in manufacturing to China's supply shock, the source of the U.S. agricultural import growth remains uncertain, posing challenges in selecting an appropriate instrumental variable. In this chapter, we choose to emphasize the international supply shock and use instruments to eliminate the effects arising from U.S. domestic demand shocks. The reason being that our objective is to investigate whether the increase in agricultural imports has spurred competition for domestic producers, it is favorable to focus on the international supply shock. Growing U.S. domestic demand leans towards the products that are unavailable, while the increasing international supply represents the source of products with comparative advantage. Despite the rapid growth of U.S. domestic demand, the top 20 suppliers have experienced even faster expansion. Figure 2.4 illustrates the trends in annual growth rates for U.S. agricultural imports from the top 20 countries, the rest of the world, and the top 20 countries' exports to the rest of the world. Over the past 25 years, U.S. agricultural imports have maintained mostly positive growth rates, with similar paces between the top 20 suppliers and the rest of the world. However, these 20 countries have seen overall faster growth in exporting to the rest of the world, primarily stemming from the economic growth of developing countries starting in the early 2000s, providing evidence for their supply shock.

It is then essential to build up an instrumental variable to eliminate this potential endogeneity issue since this omitted demand shock could be correlated with our independent variable, the county-level exposure rates, thus causing bias in our estimations. Our target is to identify the assumption that the international supply shocks, for instance, its own economic growth with rising living standards, lead to this change in import exposure. To tackle this issue, we also adapt Autor et al. (2013)'s instrumental variables strategy to properly identify the impact of trade shocks, using data from the rest of the world's imports from the top 20 suppliers to construct an instrument for changes in import demand. Table 2.2 provides informational details comparisons between the three IV identifications.

The rest of the world's imports from the top 20 countries (IV) are intuitively correlated with U.S. import exposure from these top 20 countries (independent variables). Also, they can only impact U.S. county-level outcomes (dependent variables) by affecting U.S. imports and they are not correlated with any omitted U.S.-specific supply shocks, which makes them ideal for instruments. The instrument is calculated as follows (o stands for other 10 largest exporters):

$$\Delta\mathrm{IPD}_{\mathrm{oit}} = \Sigma_{\mathrm{j}} \frac{\mathrm{W}_{\mathrm{ijt-1}}\mathrm{P}_{\mathrm{j}}}{\mathrm{W}_{\mathrm{ujt-1}}} \frac{\Delta\mathrm{I}_{\mathrm{ocjt}}}{\mathrm{W}_{\mathrm{it-1}}} \quad (2.2)$$

This non-U.S. exposure to imports from the rest of the world differs from equation (2.1) in two aspects. First, in place of U.S. agricultural imports by commodity group $\Delta\mathrm{I}_{\mathrm{ucjt}}$, it uses imports from the rest of the world to the top 20 countries $\Delta\mathrm{I}_{\mathrm{ocjt}}$. Second, in place of the start-of-period market value of agricultural products sold, this expression uses market value from the prior time period (5-year in our estimation). We use this five-year-lagged market value sold because the contemporaneous market value of agricultural products sold might be affected by anticipated trade. The use of lagged market value to apportion predicted imports from the rest of the world will mitigate this bias.

2SLS Model

We use a two-stage least squared model (2SLS), with the first stage regression constructed as follows:

$$\Delta\mathrm{IPD}_{\mathrm{uit}} = \alpha_{\mathrm{it}} + \beta\Delta\mathrm{IPD}_{\mathrm{oit}} + \mathrm{u}_{\mathrm{it}} \quad (2.3)$$

In the second stage, we estimate the effects of changes in imports per dollar on U.S. local agricultural outcomes, as follows:

$$\Delta\mathrm{A}_{\mathrm{it}} = \beta_1\Delta\mathrm{EPD}_{\mathrm{uit}} + \mathrm{X}'_{\mathrm{it}}\beta_2 + \varepsilon_{\mathrm{it}} \quad (2.4)$$

In equation (2.4), $\Delta \mathrm{A}_{\mathrm{it}}$ is the change in local outcome variables including fruit and animal-related product sales, local farm-related employment, and income variables as well as overall unemployment rate, poverty ratio, and aggregated income. Each specification is estimated using two-stage least squares (2SLS) by instrumenting the change in U.S. imports per dollar in county i ($\Delta \mathrm{IPD}_{\mathrm{uit}}$) with the change in other 10 countries' exports to China ($\Delta \mathrm{IPD}_{\mathrm{oit}}$).

Data and Descriptive Analysis

Data Sources

Our econometric approach combines data from 5 sources. The U.S. Census of Agriculture provides information on U.S. farm-related county-level outcomes, including our main estimator for our independent variable (the exposure rates), the market value of agricultural products sold, and a series of dependent variables, including fruit and animal-related product sales, farm-related employment, and income. The U.S. Bureau of Labor Statistic provides county-level data on unemployment rate and labor force, and the United States Census Bureau provides county-level aggregated income and poverty ratio. For trade data, the GATS (Global Agricultural Trade System) and UN Comtrade database provide agricultural export data from the Unites States and other countries.

We use data from each five-year interval U.S. Census of Agriculture from 1997 to 2017 from the Census Quick Stats Database. For the market value of agricultural products sold, we select the aggregated group of crop totals and animal totals with all commodities available at the county-level in the year of 1997, 2002, 2007, 2012 and 2017. Across all 50 States (including Alaska and Hawaii, Washington, D.C. excluded), there are 1,086 counties in the dataset.

Rest of the World's Imports from the Top 20 Suppliers

In Chapter 2, we construct the instrument for an international supply shock using import data from the rest of the world (excluding the United States and its top 20 suppliers). Based on data from GATS and UN Comtrade databases, ranking from their aggregated agricultural exports to China between 1997 and 2017, the top 20 suppliers we use to construct the instrument are (in alphabetical order) Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Guatemala, India, Indonesia, Ireland, Italy, Mexico, Netherlands, New Zealand, Spain, Thailand, United Kingdom, and Vietnam.

Crosswalk on Agricultural Commodities Between U.S. Census Data and Trade Data

The crosswalk we build in Chapter 1 (Appendix A) remains directly applicable. Despite the alternations in our model's composition, which now includes fewer products in the crop-related product category, the import values retrieved from GATS (FATUS Group) and UN Comtrade (HS) remain unaffected due to the fact that the excluded products hold minimal import value.

County-Level Import Exposure Rates

With all the data mentioned above available, we can calculate each county's import exposure rates. For our main estimation, we still use the growth between the year of 2007 and 2017. We selected this 10-year gap because our data limits as early as 1997. Since we use lagged terms in our instrumental variable calculation, we use 1997 to 2007 as the lagged previous decadal term. Also, it would make the results directly comparable with those in Chapter 1. Table 2.3 shows descriptive statistics for our calculated county-level export exposure rate between 2007 and 2017 ($\Delta \mathrm{IPD}_{\mathrm{uit}}$ from equation 2.1). The magnitude of this calculated change in import exposure from the top 20 suppliers is more than 4 times larger than the change in export exposures from China calculated in Chapter 1. There are in total of 1,806 counties that are exposed to imports, less than those in exports to China since we included fewer domestic products in our model. The average exposure rate is 0.1328. In the median county, the 10-year change in imports was 0.1238 from 2007 to 2017. The top counties' exposure rates are more than two times as large as the median county and the bottom county only has 33% of the median county's exposure. All observations have positive values indicating an increase in agricultural import exposure to the top 20 suppliers across all U.S. counties between 2007 and 2017.

Additionally, Figure 2.5 plots the variation in our constructed county-level change in import exposure rate to import from the top 20 suppliers between 2007 and 2017. The overall import exposure geographical distribution is similar to our import exposure. There still exists substantial variation in exposure rates across the country. The most import-exposed states include California, Florida, and Washington thanks to their heavily produced fruit and vegetables. Traditional agricultural states in the Midwest and several southern states are still highly exposed to imports, but the overall import exposure levels in these states are lower compared with export exposure to China considering that field crops are excluded.

Results

First Stage of 2SLS

To assess the efficiency of our instrumental variable, we run the first stage of the 2SLS regression. Table 2.4 presents the first-stage regression results. The first stage results suggest there exists a significant positive relationship between change in import exposure rates to the top 20 suppliers in the United States and the rest of the world's imports from these countries. A single unit increase in change in instrumental import exposure rates from the rest of the world (lagged term) would increase the import exposure rates in the United States by 0.163 units. The

R-squared number is 0.122 and F statistics easily exceed standard hurdles. The R-squared number is much smaller compared with the first stage result in Chapter 1 which is 0.842. It indicates that although the supply shock coming from these 20 suppliers exists, compared with China's contribution to the U.S. export surge, it only provides less explanation power to the import surge.

Fruit and Animal-related Products as Benchmark

We first investigate the impact of import exposure on the sales of U.S. domestic fruit and animal product. Both categories represent the most imported products while also having substantial domestic production. However, the nature of imports between these two categories is quite different and representative. In the case of fruit, foreign imports serve both as competition and complement (Karp, 2018). The increasing consumer demand for fresh produce throughout the year, led to a surge in the proportion of imported fresh fruit consumed in the United States, which exceeds 50% in 2016. Certain imported fruits, such as apples, citrus fruits, and grapes, compete with domestic producers due to factors including various consumer preferences and lower costs. In contrast, others serve to supplement the limited availability of seasonal or regional specific fruits which generates no competition. The overall import effect remains ambiguous. Regarding animal-related products, we consider beef as an example. In general, domestically produced beef does not perfectly align with the preferences of U.S. consumers (Peel, 2010). Given that the U.S. beef demand largely consists of ground beef and steaks, imported beef tends to better satisfy these preferences, thus generating competition effects. It is also the reason why the United States is the world's largest beef importer and exporter at the same time.

In Table 2.5, we analyze the effects of import exposure shocks on fruit and tree nut total sales and animal-related products total sales. The regression results find that a one-unit increase in import exposure would increase the fruit and tree nut total sales by 79.7 million dollars and decrease the animal-related product sales by 86.9 million dollars. It suggests that import exposure generates competition in animal-related product sales, and higher exposure leads to a decline in total sales. Meanwhile, higher import exposure boosts fruit sales, indicating that U.S. domestic fruit industry not only does not suffer from foreign imports but is actually benefiting from, we believe primarily, the overall growing demand for fruits.

Import Competition Influence on Local Labor Market

Table 2.6 presents initial estimates of the relationship between U.S. import exposure and U.S. farm employment. Using full samples in all 1,806 counties analyzed, the three columns of Table 2.6 provide estimates of the number of total hired workers, migrant workers[22], and unpaid workers. The specifications in Panel A, which includes no instrumental variable term, find significant negative relationships between change in import exposure and change in the number of hired workers and migrant workers. A one-unit increase in import exposure leads to a reduction of 1,326 farm-hired workers and 2,042 migrant workers. In 2SLS specifications (Panel B), when controlling for the top 20 suppliers' supply shock, the reduction in the number of hired workers further drops to 1394, with less dropped migrant worker number to 1607. The unpaid workers, which mainly consist of farm family members and partners do not see a significant impact from import exposure. In specifications where we focus on the top 50% of the counties exposed to imports, the competition effect is worsened. For the highly exposed counties, one unit of increase in import exposure would significantly decrease the number of hired workers by 3095 and even the unpaid number of workers by 737. The overall import exposure extracts its toll on farm-level

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[22] Migrant workers are defined as workers who work at a single farm location more than 75 miles from their residence location (USDA, 2023b).

employment. Farms facing more import exposure are forced to shrink their business and employment size to cut costs.

Table 2.7 shows the import exposure effects on producers who manage and operate the farm. Similarly, we find evidence that increasing import exposure would result in a shrink in farm employment. The coefficient in column (1) indicates that a one-unit increase in import exposure is predicted to reduce farm producers by 235, male producers by 91.2, and female producers by 143. We expected to observe variations in the change of the number of producers across racial groups, given the fact that States such as California and Florida, which often have a high number of minority farm workers, experienced greater import exposure. However, the results are proved to be statistically insignificant.

Confirming the facts that rising import exposure led to declines in farm-related employment, we further investigate its impact on the general unemployment rate and total labor force. Table 2.8 summarize the 2SLS regression result between import exposure from the top 20 suppliers and county-level unemployment rate and labor force number. In contrast with farm-related employment, higher import exposure has reverse effects on the general labor market. The coefficient of -1.932 and 34750.7 indicates that a one-unit increase in import exposure is predicted to reduce the unemployment rate by 1.932 percentage points and increase the number of workers by 34750. This suggests some evidence of industry shifts. As import exposure rises, domestic farm workers and producers face increased competition from imported goods, resulting in a reduction in the demand for their labor. Meanwhile, the acquisition of imports and growing domestic demand creates new job opportunities in other industries including retail and service, compensating for the loss in farms and the agricultural sector.

Income-related Outcomes

Beyond employment impacts, it is more intuitive to investigate income changes stemming from import exposures. Each column of Table 2.9 provides results from the estimation between import exposure from the top 20 suppliers and one farm income-related outcome. Our estimates show statistically significant and high-level effects of import growth on these variables, between the period of 2007 and 2017. We find that growing import exposure led to significant decreases in all-source U.S. net farm income, government program payment, and increases in total farm production expenses.

Column (1) shows the results between import exposure and net farm income, with each unit-level increase reducing average county-level net farm income by $80.3 million. Given that there are 1806 observed counties in our data, we estimate the average import exposure reduces net farm income to U.S. producers by $19.2 billion, annually, accounting for more than a quarter of U.S. net farm income in 2017 at $75.1 billion. Column (2) shows the results of the import exposure effects on total farm production expenses, with each one-unit increase raising average farm production by more than $118.7 million in 2017 nominal dollars or 0.531 percentage points. Annually, the average level of import exposure for all observed counties generates a $28.5 billion increase in expenses, representing 8% of U.S. total expenses. Column (3) shows a negative relationship between import exposure and government program payments. A one-unit level increase would cost the average government payment by more than $12 million or more than 1.8 percentage points. With all observed counties, the annual total lost is $2.8 billion, taking up 0.7% of U.S. total.

These results indicate that U.S. county-level agricultural import exposure has direct competition effects and negatively impacts farm-level profitability, which is often overlooked.

Similar to the manufacturing industry, although to a much smaller degree, the supply shock from these 20 international major suppliers results in import competition to domestic producers. However, the damage created by manufacturing was never mitigated (Autor et al., 2013) because manufactured goods imports do not create the same level of opportunities, employment, and domestic demand growth for factory workers. Thus, similar to farm-related employment, in Table 2.10 we examine the overall county-level aggregated income and poverty ratio from all sources. The results show that although imports bring competition to domestic producers, the cost is likely absorbed in other sectors.

Table 2.10 summarizes the effect of import exposure on county-level aggregated income and poverty ratio. Similar to farm-related employment, rising import exposure has a strong and positive impact on aggregated income and a negative impact on the poverty ratio. A one-unit increase in import exposure would result in an increase in aggregated income by more than $14 billion, well covering the loss in net farm income. It would also lead to an 11.576 percentage point decrease in the poverty ratio. The average increase in import exposure is 0.1328 units, meaning that on average, U.S. county-level poverty rate drops by 1.54%.

These results indicate that even though import exposure create competition, the U.S. society on an aggregate level is gaining from rising import exposure. This could stem from (1) better consumer access on a broader range of products, offered at lower prices due to increased competition among suppliers. This access allows consumers to improve overall living standard and contribute to the reduction in poverty rates, (2) enhanced productivity. Increased import exposure can stimulate domestic producers to improve their efficiency and productivity to stay competitiveness, which reflects on the shrink of farm-related employment and increasing production expenses, (3) employment opportunities shift to other industries. As the United States as a country imports more agricultural goods, its economy tends to shift to high-value-added industries and service sectors. These sectors are overall more profitable compared with traditional agriculture, (4) export growth. More imports can in return stimulate exports as the country now has access to intermediate goods services, which domestic firms utilize as inputs for their own production for exports.

Conclusions

Unlike agricultural exports that take the center stage in U.S. trade related discussions, imports never receive the same level of attention. Continuing its growth for more than five decades, U.S. agricultural imports have been quietly affecting many aspects of trade landscape. In this Chapter, following a similar but modified county-level exposure rate construction method, we examine how agricultural imports have been affecting U.S. domestic agricultural outcomes.

Our target shifts from China to top 20 international suppliers of U.S. agricultural imports. We modify our methodology by (1) recomposite the structure of products included to isolate the import effects on just the products with substantial domestic production, (2) adding a weight term to balance the unbalanced domestic production value between crop-related products and animal-related products, (3) changing our instrumental variable to the rest of the world's import from these 20 countries to account for their supply shock.

The constructed import exposure shows four times as large in magnitude compared with the export exposure to China, with less counties observed. Geological distribution is close to the export exposure map. Variation in different counties remain large. States with more fruit and vegetable production show improving exposure compared with traditional field crop production heavy states.

In our 2SLS estimation results, we find increasing import exposure result in increase in fruit sales but reduction in animal-related product sales. We find that import exposure strongly and negative impacts local farm-related employment and income, but the society's overall employment rate and income are positively connected with import exposure, indicating the existence of import competition. But the damage caused is likely absorbed by other industries and the aggregated influence from import exposure is beneficial.

Table 2.1. Selected U.S. Agricultural Imported Products Based on BICO Product Groups from FAS of USDA[23]

Group Name	Selected Products
Bulk	Wheat, Coarse Grains, Rice, Tobacco (Unmanufactured), Coffee (Unroasted), Cocoa Beans, Tea, Oilseeds
Intermediate	Live Animals, Other Livestock Products, Vegetable Oils, Planting Seeds, Sugars, Essential Oils
Consumer-Oriented	Beef, Pork, Other Meat, Dairy Products, Fresh Fruit, Fresh Vegetables, Wine, Beer, Spices, Chocolate and Cocoa Products, Baked Goods, Dog and Cat Food, Manufactured Tobacco

Table 2.2. Shocks, Endogeneity, and IV Identifications

Reference	Shock Observed	Industry	Desirable Source	Endogeneity Source	IV
Autor et al. (2013)	U.S. Imports from China Increase	Manufacturing	China's Supply Shock	U.S. Demand Shock	China's Export to Other Eight High-Income Countries
Chapter 1	U.S. Exports to China Increase	Agriculture	China's Demand Shock	U.S. Supply Shock	China's Import from Other 10 Largest Exporters
Chapter 2	U.S. Imports from Top 20 Suppliers Increase	Agriculture	U.S. Demand Shock	Top 20 Suppliers' Supply Shock	Rest of the World's Imports from Top 20 Suppliers'

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[23] Source: Global Agricultural Trade System (GATS) from USDA

Table 2.3. Descriptive Statistics for Calculated Change of Agricultural Import Exposure Rates from Top 20 International Suppliers, 2007-2017[24]

Panel A. Percentiles				
90th Percentiles	75th Percentiles	50th Percentiles	25th Percentiles	10th Percentiles
0.2354	0.1901	0.1238	0.0666	0.0506
Average				
0.1328				
Panel B. Largest and Smallest Values among All Counties				
Top 5				
San Francisco, CA	Richmond, NY	New Madrid, MO	Lake, TN	Tensas, LA
0.2655	0.2655	0.2654	0.2651	0.2649
Median				
Jay, IN				
0.1238				
Bottom 5				
Gilpin, CO	Hinsdale, CO	Jackson, CO	Summit, CO	Shoshone, ID
0.0464	0.0464	0.0464	0.0464	0.0464

Table 2.4. First Stage Regression Results of 2SLS, Full Sample

	$\Delta \mathrm{IPD}_{\mathrm{u0717}}$
	(1)
$\Delta \mathrm{IPD}_{\mathrm{o9707}}$	0.163***
	(0.010)
N	1,806
R square	0.122
F-Stat	250.546***

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

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[24] Note: Table reports change in 10-year values of exposure rates between 2007 and 2017 in the aggregated market value of agricultural commodities sold per dollar of import, which is a unit-free ratio.

Table 2.5. Imports from Top 20 Suppliers and Change of Fruit and Animal-related Products Total Sales in U.S. Counties, 2007-2017, 2SLS Estimates

	ΔFruit and Tree Nut Total Sales in 2017 Real Dollar (1)	ΔAnimal Products Total Sales in 2017 Real Dollar (3)
ΔIPD_{u0717}	79,712,977***	-86,919,105**
	(40,380,967)	(35,070,866)
R-squared	0.005	0.022

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

Table 2.6. Imports from Top 20 Suppliers and Change of Different Types of Farm Workers in U.S. Counties, 2007-2017

	ΔHired Workers (1)	ΔMigrant Workers (2)	ΔUnpaid Workers (3)
Panel A. OLS Estimates, Full Sample			
ΔIPD_{u0717}	-1,326.5***	-2,042.7*	-93.9
	(272.0)	(1,044.1)	(227.9)
R-squared	0.014	0.004	0.002
Panel B. 2SLS Estimates, Full Sample			
ΔIPD_{u0717}	-1,394.0***	-1,607.8**	-52.7
	(260.5)	(675.6)	(174.8)
R-squared	0.017	0.006	0.003
Panel C. 2SLS Estimates, Top 50% Sample			
ΔIPD_{u0717}	-3,095.5***	-2,840.9	-737.4*
	(967.1)	(4324.4)	(427.9)
R-squared	0.013	0.001	0.004

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

Table 2.7. Imports from Top 20 Suppliers and Change of Producers in U.S. Counties, 2007-2017, 2SLS Estimates

	ΔAll Producers (1)	ΔMale Producers (2)	ΔFemale Producers (3)	ΔWhite Producers (4)	ΔMinority Producers (5)
ΔIPD_{u0717}	-235.4***	-91.2*	-143.0***	-230.5	228.9
	(85.3)	(51.4)	(46.4)	(225.5)	(225.5)
R-squared	0.005	0.002	0.006	0.003	0.003

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

Table 2.8. Imports from Top 20 Suppliers and Change of Unemployment Rates and Labor Force in U.S. Counties, 2007-2017, 2SLS Estimates

	ΔUnemployment Rate (1)	ΔLabor Force (1)
ΔIPD_{o9707}	-1.932***	34,750.7***
	(0.394)	(6032.6)
R square	0.013	0.018

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

Table 2.9. Imports from Top 20 Suppliers and Change of Income-Related Outcomes in U.S. Counties, 2007-2017: 2SLS Estimates

	ΔNet Farm Income in 2017 Real Dollar (1)	ΔTotal Farm Production Expenses in 2017 Real Dollar (2)	ΔGovernment Program Payment in 2017 Real Dollar (3)
Panel A. Percent Change,			
$\Delta\text{IPD}_{\text{u0717}}$	-0.455	0.531***	-1.885**
	(1.946)	(0.109)	(0.779)
R-squared	0.003	0.014	0.004
Panel B. Dollar Change			
$\Delta\text{IPD}_{\text{u0717}}$	-80,330,361***	118,767,646***	-12,092,032**
	(9,018,583)	(24,467,904)	(2,213,283)
R-squared	0.046	0.014	0.003

*** Significant at the 1 percent level

** Significant at the 5 percent level

* Significant at the 10 percent level

Table 2.10. Imports from Top 20 Suppliers and Change of Income and Poverty Variables in U.S. Counties, 2007-2017, 2SLS Estimates

	ΔAggregated Income in 2017 Real Dollars (1)	ΔPoverty Ratio (2)
$\Delta\text{IPD}_{\text{o9707}}$	14,135,297,482***	-11.576***
	(2,719,914,755)	(3.780)
R square	0.046	0.120

*** Significant at the 1 percent level

** Significant at the 5 percent level

* Significant at the 10 percent level

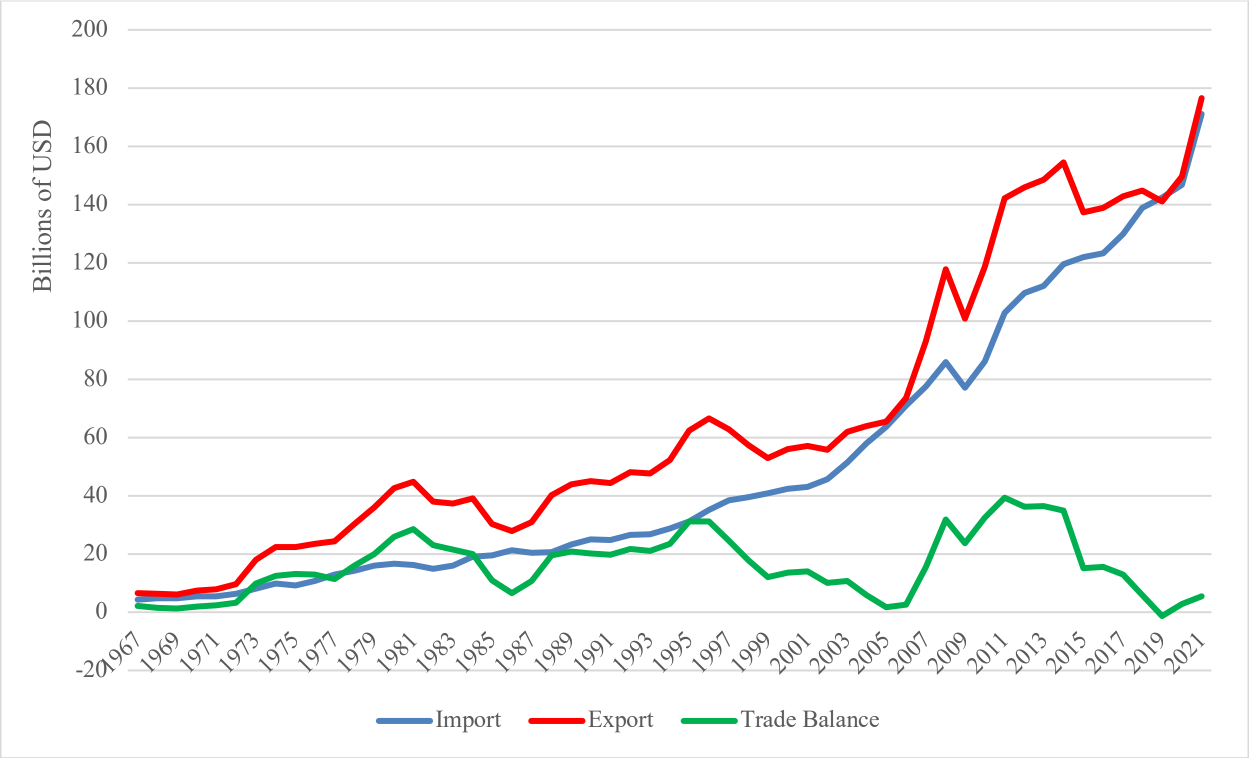

Figure 2.1. U.S. Agricultural Imports, Exports, and Trade Balance, 1967-2021[25]

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[25] Source: Global Agricultural Trade System (GATS) from USDA and U.S. Census Bureau International Trade Database

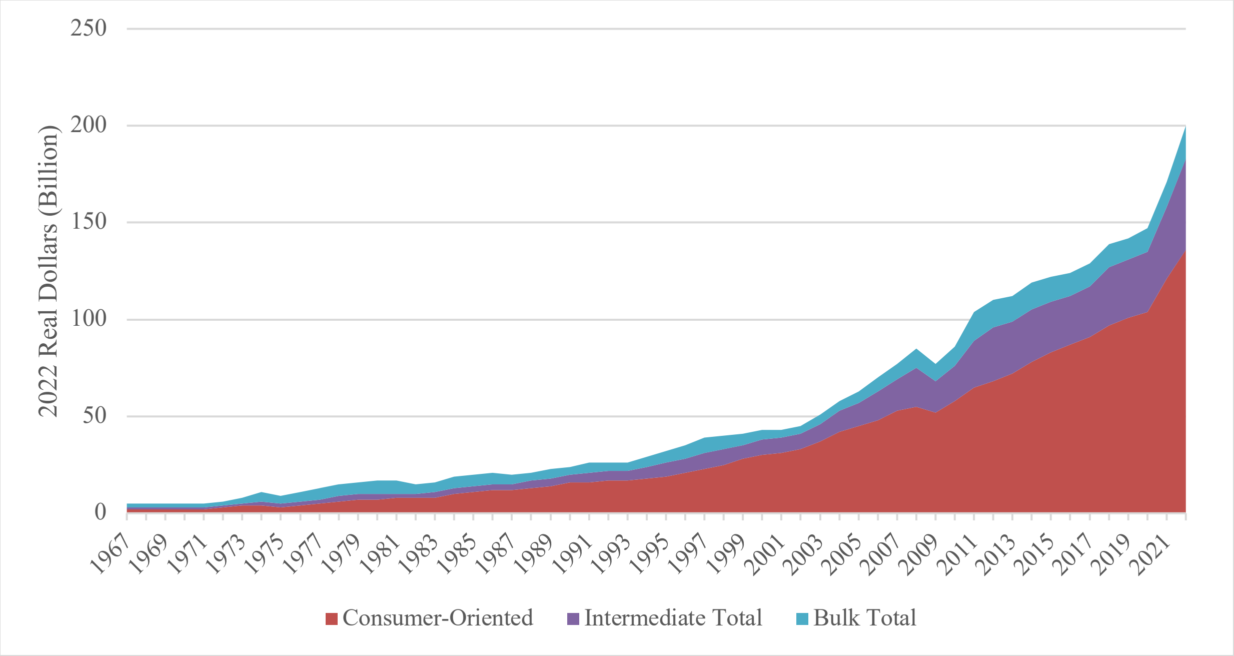

Figure 2.2. U.S. Agricultural Imports by BICO Groups, 1967-2022, in 2022 Real Dollars[26]

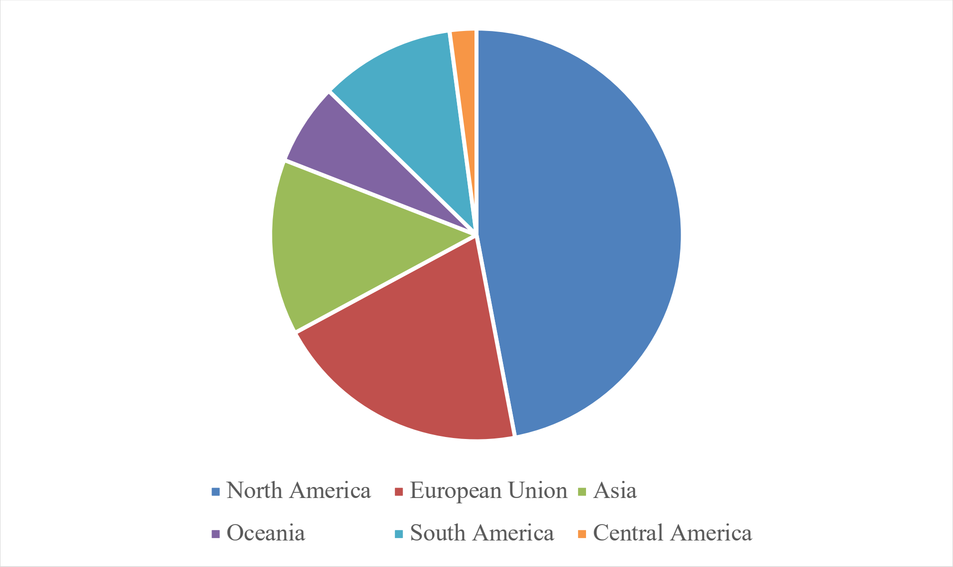

Figure 2.3. Origins of U.S. Agricultural Imports, Top 20 Countries by Regions, 2007-2017[27]

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[26] Source: Global Agricultural Trade System (GATS) from USDA

[27] Source: Global Agricultural Trade System (GATS) from USDA

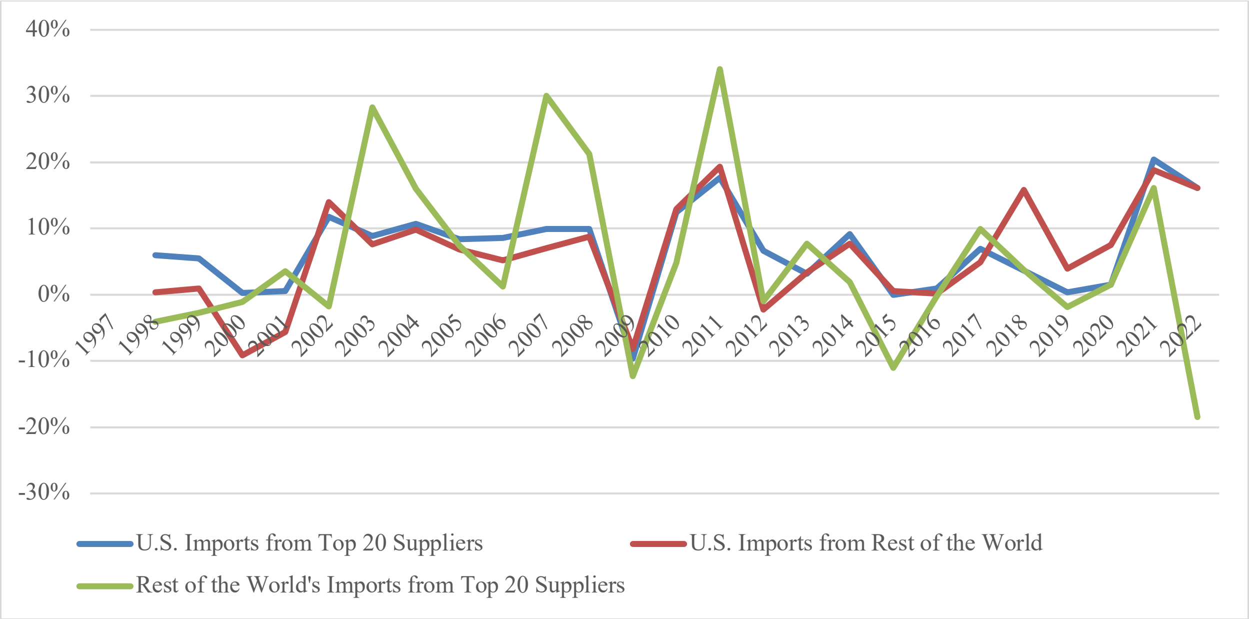

Figure 2.4. The Trends of U.S. Agricultural Imports from Top 20 Suppliers and the Rest of the World, and the Rest of the World's Imports from Top 20 Suppliers, in Trillion USD, 1997-2022[28]

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[28] Source: Global Agricultural Trade System (GATS) from USDA

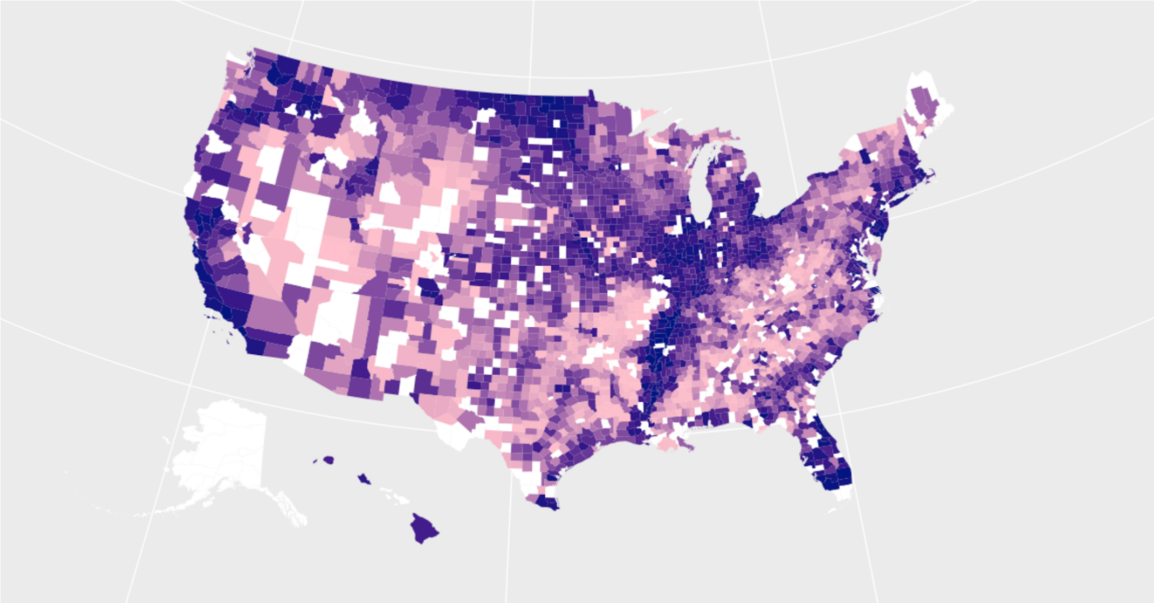

Figure 2.5. U.S. County-Level Import Exposure Rates from the Top 20 Suppliers[29]

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[29] Note: Darker colors represent greater levels of exposure.

CHAPTER 3

U.S. COUNTY-LEVEL IMPACTS OF NET AGRICULTURAL TRADE EXPOSURE

Motivation Revisit

In Chapter 1 and 2, we focus on examining the effects of both sides of U.S. agricultural trade, the effects of export exposure to China and import exposure from the top 20 international suppliers on the U.S. domestic outcomes. We analyze the potential consequences on local production, acreage, income, and labor. As a conclusion, we find that rising export exposure largely benefits U.S. local agricultural outcomes. Meanwhile, import exposure increase creates competitions in certain areas, especially on local farm level employment and income, although the cost is overall absorbed by other industries. While both sides of trade exposure provide us with different perspectives, to gain a more comprehensive understanding of the overall effects of trade exposure on the U.S. agricultural landscape and its trends, it is essential to analyze the net effects of trade exposure in the U.S. across the world and essential products.

The motivation stemmed from the facts behind U.S. manufacturing industry. Even though theoretically, more and more liberalized trade, thanks to globalization, can influence domestic outcomes (e.g., income and employment) by trading with any countries, trade theory believe that low-wage countries can cause certain disruptions in high-wage countries' labor markets (Krugman, 2000; 2008). Historically, U.S. imports are limited originating from low-wage countries. But the fact changed when China joined the WTO in 2001, it brought import shocks to all high-income countries in the world. The declines in U.S. manufacturing wage and employment sparked heated discussion in how rising Chinese imports contribute to these consequences in the manufacturing industry (Autor et al. 2013, 2014, 2020; Acemoglu et al., 2016; Bernard et al., 2006; and Pierce and Schott, 2016), as well as other aspects including innovations (Bloom et al., 2015) and from other high-income countries (Yamashita., 2017).

The second milestone event is the recent U.S.-China trade war episodes. Starting in 2018, the Trump administration initiated a series of tariffs on multiple trading partners, including China, Canada, Mexico, and the European Union, and received reactions from these partners in the form of retaliatory tariffs (Bown, 2021). What's interesting is the existence of political motivations behind the trade war. Many of the retaliatory tariffs target U.S. agricultural products, which affect rural counties that are the base of Republican votes (Fajgelbaum and Khandelwal, 2021). As a result, in August 2018, the Trump administration announced the Market Facilitation Program (MFP) aiming to compensate the farmers affected by the tariffs in the form of direct payments. This manipulation of fiscal tools also invited a series of literature concerning that payments from the MFP were not distributed based on the true loss level among counties and there are political considerations behind (Adjemian et al., 2021; Amiti et al., 2020; and Janzen and Hendricks, 2020). What's more concerning is that all these trade disputes, despite its political motivations behind, have eroded public faith in trade (Amiti et al., 2019; Bown and Zhang, 2019; and Davis and Meunier, 2019).

How agriculture serve in the system of U.S. trade overall has been often neglected before the trade war. Retaliatory tariffs that target agricultural products provide evidence that the agriculture sector is where the U.S. has been gaining advantages. This Chapter studies U.S. county-level responses to growing trade exposure, not only in exports or imports, but in the aggregated level of both sides of trade. We map the incremental changes in trade exposures for the past 25 years in the United States and document responses between different length of time periods.

Understanding how U.S. local outcome respond to trade exposures helps inform the positivity of trade and implications of trade policy.

A major empirical challenge is the construction of net trade exposure. We follow Autor et al. (2013) and Choi and Lim (2022) to create our own net trade exposure model. Differed from the previous methodology utilized in Chapter 1 and 2, we difference the county-level proportioned contribution factor from exports and imports between any two discontinued time periods (not a continued time series) from 1997 to 2022, dividing by the county's population to construct a county-level aggregated trade exposure. We employ a different set of products at HS 6-digit level, constructing each product with its own import or export differences instead of aggregating to crop-related and animal-related products. We also explore deeper into the crosswalk between U.S. Ag Census data and the HS 6-digit level code to match each product individually.

We present three core findings: 1) net trade exposure rates show less variation across U.S. counties compared with export and import exposures. And the trade war deeply challenged the net trade exposure rates. 2) net trade exposure largely benefits U.S. county-level aggregated net farm income and agricultural employment share of total working age population, across all 5-, 10-, and 15-year periods. 3) net trade exposure change between 2017 and 2019 positively affects county-level Republican vote share in the 2020 U.S. Presidential election.

This Chapter builds on Chapter 1 and 2 and several recent studies that link domestic local outcomes with trade exposure. It goes one step further in several strands of literature. First, it contributes to the literature on trade and exposure by providing a broader picture from both imports and exports sides of trade with more nuanced and quantified responses on local outcomes level that may help reconcile contradictory findings in certain other industries or one side of trade

(Melitz, 2003; Bernard et al., 2007, and Bustos, 2011). Second, it contributes to the literature on trade and local labor market. The overall positive results on income and employment are consistent with the findings in previous Chapters. Our evidence shows increasing trade exposure have reverse effects compared with the manufacturing industry. Thirdly, it contributes to the literature of trade exposure with political economy where trade-related policies are immensely studied for its political impacts.

The rest of the Chapter is organized as follows. Section 2 describes the empirical methodology. Section 3 provides data sources and the trendline in trade exposure among different periods. Section 4 presents regression results on local employment and income. Section 5 examines political votes and trade exposure, and Section 6 concludes the Chapter.

Methodology Redesign

Exposure to Trade Shocks

There have been many designs in constructing the trade exposure variable. The original model developed by Arkolakis et al. (2012) adopted a gravity framework to analyze how changes in trade quantities impact labor-market outcomes. In this model, small regions are treated as individual small open economies, enabling the derivation of regional effects that are proportional to changes in national-level trade quantities. Both traded and non-traded goods exist within these individual economies and the inter-economy labor migration is ignored.

$$\Delta L_{T_i} \ or \ \Delta W_{T_i} = \rho_i \sum_j C_{ij} \frac{L_{ij}}{L_{N_i}} [\theta_{ijC} \Delta E_{cj} - \sum_k \theta_{ij} \emptyset_{Cjk} A_{Cj}] \ (3.1)$$

This model breaks the appeared trade shock into two sources: 1) rising competition driven by other countries' increasing supply capability, and 2) increasing domestic demand. See equation 3.1, the source from international supply is captured by other countries supply capability in exports

(A_{Cj}) times its initial share θ_{ij}, representing a specific country k's output in individual economy *i,* shipping to each market, then times the initial imports from country k's share of economy i's total import expenditure $\emptyset_{Cjk}$. The second source of increasing domestic demand is captured by the first difference change in total expenditure E_{cj}. Lastly, to map the total shock (summed across different sectors) observed down on each individual economy, this model weighs the initial ratio of employment of economy i in the entire country as $\frac{L_{ij}}{L_{N_i}}$, plus a general-equilibrium scaling factor C_{ij} and a trade imbalance in total expenditure factor ρ_i.

What's worth mentioning is that a trade shock is usually defined as an abrupt change in trade quantities within a specific period, examples including both the U.S. agricultural import and export surge since the early 2000s. One could argue that a time-series model can better capture the causality nature behind increase in trade exposures and local outcome changes. However, as trade shocks being continuously observed, it's not ideal to assume the stationarity of changing exposures. First difference model can be utilized to remove decades-long trend or seasonality and make the estimation process more appropriate.

Autor et al. (2013)'s methodology simplifies this gravity model. They consider the small economy i in the concept of Commuting Zone (CZ), which is a clustering method in grouping counties to define local labor markets. Ideally this CZ grouping method is better suited to study for manufacturing employment effects as counties within the same CZ tend to share similar characteristics. They ignored the trade imbalance factor and presented their exposure expression in equation 3.2.

$$\Delta IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}} \quad (3.2)$$

Country k in this case is China specifically. The China supply effect is captured by dividing the start-of-period employment L_{it}. The point-to-point change in exports to China ΔM_{ucjt} captures internal demand change. This simplified model is simple to follow and manipulate on the data level, therefore adopted by many following researchers to study effects of trade shocks in the form of exposure on local outcomes.

Exposure Construction Adaptation in Agriculture

To the best of the author's knowledge, we are the among first to attempt to adopt Autor et al. (2013)'s model into agriculture starting in the year as early as 2017. Due to the occurrence of trade war and the attention it gathered upon agriculture, literature began to utilize this model in analyzing the shocks observed from China's retaliatory tariffs (Blanchard et al., 2022; Choi and Lim, 2022).

The changes that need to be made to the model, however, are quite different compared to previous literature discussing the manufacturing industry. Four aspects of Autor et al. (2013)' model can be adjusted. First is the geographical local estimation unit. Commuting Zones capture the clustered counties' manufacturing-wise characteristics well but the variance in production nature between U.S. counties in agriculture is large. Geographically adjacent counties do not necessarily share similar production and employment patterns. Thus, county-level estimation is more ideal than commuting zones for agriculture.

Second is the weight measurement where they use each Commuting Zone's manufacturing employment ratio $\frac{L_{ijt}}{L_{ujt}}$ to account for their individual contribution to total export change and then sum across industries. Blanchard et al. (2022) kept this employment ratio method when looking into the China retaliatory tariff shock by utilizing the county's national employment share in the

NAICS 3-digit industry and aggregating across industries. The concern is that, in agriculture, it is intuitive that it is inappropriate to map each county's contribution to trade by their U.S. national employment ratio because the county's contribution to total trade changes reflects on their agricultural production value, and the value of production, however, does not necessarily reflect on farm employment (Fisher and Knutson, 2013). Besides, aggregation on industry variations for sure creates bias in estimations regarding U.S. agricultural trade. Product level variation is the primary source contributing to U.S. import/export changes, for example, soybeans in exports and beef in imports. In 2017, we proposed to use the national proportion of each county's total acres harvested as the measurement of weight and then sum across each individual crop categories. The results were not satisfying, primarily because although acres harvested accurately captures changes in field crops, where products including soybeans, wheat, and sorghum are the dominating components of U.S. agricultural exports, it fails to capture the whole picture where animal-related products also contribute heavily. Also, the lack of mapping each single crop categories' production data from U.S. Agricultural Census results in estimation errors. As a solution, we proposed (in 2019) using county-level market value sold of each product category, calculating their national shares, aggregating each individual product, to account for county-level contributions to national import/export change, which is the methodology we use in Chapter 1 and 2, later seen on Choi and Lim (2022). The advantage of this method is that it captures all products available (not just limiting to field crops) and can proportionally and correctly reflect the county-level production value contributions to the national level. For many products, not just animal-related products, including fruit and vegetable, value is a better unit compared with acres when it comes to production values. Also, aggregating on each individual products ensured to capture the variance generated from imbalanced weight in trade values.

The third aspect that is subject to change is the first difference change in trade values ΔM_{ucjt}. both Blanchard et al. (2022) and Choi and Lim (2022) replaced the direct difference in export values with the change in tariff rates times the change in exports, which is essentially the same logic but with a focus on shocks generated by tariffs. This change in trade value expression is broadly accepted by other researchers. The fourth part is the dividing unit L_{it} from equation 3.2, which divide the previously calculated proportioned change in trade values by the employment in this county to generate the "change in import per worker (\$/worker)" ratio as the measurement of exposure. In Chapter 1 and 2, we utilize the county's total agricultural product value sold as this denominator. And our exposure is expressed in "change in export/import per dollar (\$/\$)" which gives us a unit-free ratio. It translates our exposure into that for every dollar the county created from selling agricultural products, the proportion of this dollar that contributes to imports/exports. Blanchard et al. (2022) and Choi and Lim (2022) used the county's population to express their exposure in \$/person.

Total Trade Exposure Construction

Considering all aspects introduced, following Autor et al. (2013) and Choi and Lim (2022), in Chapter 3, we measure the county-level total (aggregated) trade exposure as follows:

$$\Delta TPP_{c,t_2-t_1} = \frac{1}{L_c}\left(\sum_e \frac{V_{ec}}{V_e}\Delta E_{e,t_2-t_1} - \sum_i \frac{V_{ic}}{V_i}\Delta I_{i,t_2-t_1}\right) \quad (3.3)$$

ΔTPP means change in trade per person, where *c* refers to a county, t_1 and t_2 represents the beginning and ending year of desired estimation. *i* and *e* each refers to a unique set of products of U.S. agricultural imports and exports that are most representative and cover most of the trade values. V_{ec} and V_{ic} are the market value sold of each product category on county-level. V_e and V_i are the U.S. total market value sold of each product. $\Delta E_{e,t_2-t_1}$ and $\Delta I_{i,t_2-t_1}$denote the first difference change in export/import values between period t_1 and t_2 for each product corresponding to the product set i and e. We difference the aggregated (on product levels) trade shocks for a county between exports and imports to calculate the net trade effects, then divide by the population of the county, to generate our total trade exposure.

This measurement differs with our previous methodology in Chapter 1 and 2 in several ways: 1) it calculates the difference between export effects and import effects. By acknowledging the gaining/excessive domestic supply through export effects, it also accounts for the competition/unfulfilled domestic demand through import effects, providing a net trade effect estimation. 2) We use aggregation on each individual product level instead of combining all products into crop-related and animal-related product categories to better account for individual product variances. 3) We use population instead of the county's total agricultural product value sold as the denominator.

One could argue that this measurement undermines the exposure level of counties that produce certain products that both have massive increase in imports and exports and emphasize on the negativities of imports. However, the intention of this measurement is to find the net balance of trade effects to provide an overall picture of agricultural trade effects. Here we assume import as a source of competition and we, again, only include imported goods that have domestic production. In Chapter 1 and 2 we emphasized on export and import effect respectively. Although imports do not reflect heavy cost on U.S. general employment and income, increase in change in import exposure on the farm level bring opposite results compared with exports. Suppose one county is producing a product that is both importing and exporting, the net trade effects for this specific product should be diminished on the aggregated net level since the income and employment gains from exports would likely be offset by import competitions.

Data Overview

Data Sources

Compared with our first two Chapters, our econometric approach combines data from more sources. The U.S. Census of Agriculture provides information on U.S. farm-related county-level outcomes, including our main estimator for our independent variable (the exposure rates), the market value of agricultural products sold, and our dependent variable, the county-level net farm income. For other dependent variables, the United States Census Bureau provides county-level agriculture-related employment ratio among the working age population. The county-level Presidential vote shares combine the source from David Leip's Election Atlas and the election data lab from MIT.

For trade data, the GATS (Global Agricultural Trade System) and UN Comtrade database provide agricultural import and export data from the Unites States and other countries.

We use data from each five-year interval U.S. Census of Agriculture at the county-level in the year of 1997, 2002, 2007, 2012 and 2017 for the market value of agricultural products sold and a couple of other dependent variables including net farm income and employment, across all 50 States (including Alaska and Hawaii, Washington, D.C. excluded), the number of available counties vary depend on the period focused. We apply CPI difference in all dollar value involved in our dataset and use 2017 real dollars.

Product Selection and Crosswalk Update

The products that we consider for the net trade effect is more delicate compared with those in Chapter 1 and 2. Instead of combining products into crop and animal related products categories, in practice, we choose a set of products that (1) represent the most import/exported products in U.S. agricultural trade, (2) are reliable to utilize the crosswalk with their own domestical production data from Ag Census. In Chapter 1 and 2, by grouping products into two major categories left some margin of error when calculating the difference in imports/exports. But when aggregating through each single product category, we must exercise caution to avoid any bias caused by the crosswalk.

Appendix C presents the crosswalk between HS 6-digit code and Ag Census product categories used in Chapter 3. For exporting products, we select 16 products under the HS 6-digit classification. These 17 products combined account for 70% of the total U.S. agricultural export growth since 2000. Their aggregated export value together has accounted for more than 60% of total U.S. agricultural export amount for more than 15 years. They can be precisely identified in Ag Census' product categories and are categorized into 11 individual groups. For importing products, there are in total of 8 product categories, representing 67% of total U.S. agricultural imports in 2017. Domestically, they are further mapped into 8 Census' product groups. Although all import products seem to be included in the same set of the exporting products, the actual composition of HS codes are different. It's important to note that is that there are numerous missing values for the market value of products at the county level in the Ag Census dataset. Observations that are recorded as "(D)" indicate that data for individual operations was withheld to protect confidentiality. Additionally, some observations are recorded as "(Z)" due to data quality concerns.

Control Variables

In Chapter 3, we also include a rich set of U.S. county-level control variables to control for industry and demographic characteristics. Because one of our primary dependent variables is income, hence economic-related controls are excluded. The data come from the American Community Survey (ACS) developed by the U.S. Census Bureau. We use ACS 5-year estimates in year 2010, 2012, and 2017 to control for each pre-exposure periods. The advantage of the 5-year estimates is that it takes the observations collected in a 5-year period. It provides a more comprehensive view of the data by pooling information across a longer time span. For exposure period starting in 2007, we use the five-year average estimates from 2010. For exposure period starting in 1997 and 2002, we are not able to apply these control variables due to data availability.

Appendix D shows the summary statistics for these control variables. We control for industry characteristics using county-level sectoral employment share at two sectors including "agricultural and mining", and "manufacturing". For demographical characteristics, we control for county-level with population share in gender, age, and race levels.

County-Level Distribution of Net Trade Exposure

In Chapter 3, as we do not utilize the instrumental variable strategy, a lagged term from period 97 is not necessary. We choose to control for endogeneity through control variables. It thus allows us to observe changes in net trade exposure between any two periods, with the start-of-period in 97, 02, 07, 12, and 17, and the end-of-period in any afterwards years before 2022. Appendix E include all U.S. County-level maps for all 5-, 10-, and 15-year periods available. Figure 3.1 shows the county variation in changing net trade exposure between 2007 and 2017, the same period that served as the main estimation for Chapter 1 and 2. A darker purple represents larger positive net trade exposure and pink indicates low or negative net trade exposure. The overall exposure distribution is quite different compared with those in Chapter 1 and 2. Counties in Great Plains, which is the major U.S. crop production area, show the strongest net exposure. Heavy fruit and vegetable producing, and some soybean heavy producing States are less exposed compared with considering only one side of trade.

Figure 3.2 demonstrates the net trade exposure change between the 2008 economic recession and the 2018 trade war periods. In 2008 recession, both U.S. agricultural imports and exports saw decline at similar level in values. Therefore, the net exposure impact to most counties is not substantial. However, in 2018 trade war period, we can clearly observe that most U.S. counties witnessed dramatic declines in net trade exposure, primarily due to the stall in exports and steadily increasing imports.

Net Farm Income and Agricultural Employment

Net Farm Income and Net Trade Exposure

We first analyze how net trade exposure affect net farm income over different time periods. The first-difference regression model is as follows:

$$\Delta NI_{c,t_2-t_1} = \beta \Delta TPP_{c,t_2-t_1} + \gamma \Delta NI_{c,t_1-t_0} + \theta X_c + \psi_s + \epsilon_c \text{ (3.4)}$$

Where c denotes county. $\Delta NI_{c,t_2-t_1}$refers to change in net farm income between period t_1 and t_2. $\Delta TPP_{c,t_2-t_1}$denotes the change in net trade exposure per person between t_1 and t_2. In addition, we include the net farm income difference in a previous period $\Delta NI_{c,t_1-t_0}$between t_0 and t_1 to control for any pre-existing trend net income change trend[30]. Because our model here in Chapter 3 do not utilize an instrumental variable strategy, it's important to control for endogeneity. Thus, we also include a rich set of control variables X_c to control for county-level characteristics. These measures to control for time-invariant county-level characteristics include first-difference, control for pre-existing trends and control for county-level industry and demographical characteristics should be able to control for endogeneity and justify our model causality. Lastly, we also control for state fixed effects through ψ_s.

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[30] Only for periods starting 2007 and later due to data availability.

Table 3.1 shows the estimation results for both 10-year intervals and the 15-interval from 2002-20012, 2007-2017, and 2002-2017. Across all columns in Table 3.1, the impacts of change in net trade exposure on change in net farm income in the same periods are almost all positive and statistically significant at 1% level. Take period 2007-2017 as an example, the coefficient 4,019.1 in column 5 indicates that a $1 exogenous 10-year increase in a county's net trade exposure per person is predicted to increase net farm income by 4,019.1 dollars. The estimates across all periods are similar in magnitude and all three models show stable statistical relationships.

In period 2002-2012, the estimated coefficients are larger, with the reason being that export value difference between 2002 and 2012 is dramatic (after China joined the WTO in 2001) and outgrows the growth in import increase. A concern for this analysis is that this consistent positive relationship could stem from the fact that both net trade exposure and net farm income experienced substantial increase in a longer time span. In order to ascertain that our results accurately capture the period-specific influences of net trade exposure, rather than a persistent underlying long-run common causal element behind both increase in net farm income and net U.S. trade values, we conduct a falsification assessment to conduct the regression in shorter time spans, where the changes in net farm income and net U.S. agricultural trade were almost idle.

Table 3.2 shows the correlation between change in net trade exposure and change in net farm income in all three 5-year periods. The U.S. agricultural trade balance increased from around $10 billion to more than $30 billion in 2007 in surplus. However, the surplus stayed below $40 billion in 2012 and declined to less than $20 billion in 2017, a lower level compared to 2007 and 2012. Meanwhile, the U.S. net farm income stayed on a very consistent level with almost no changes in 2007, 2012, and 2017 (all around 9 billion in 2017 real dollars). However, results from Table 3.2 still exhibits strong positive statistical relationships between change in net trade exposure and change in net farm income (almost all statistically significant at 1% level) and the magnitude are similar with the results in 10- and 15-year periods results. With added State-level fixed effects, county-level demographical controls, comparisons across all time spans under different economic backgrounds, these correlations provide little evidence of endogeneity and reverse causality.

Agricultural Employment and Net Trade Exposure

Following the similar logic, we expect that rising net trade exposure would lead to increase in agricultural employment share. The model we use is the same with analyzing net farm income, as shown in equation 3.5.

$$\Delta AES_{c,t_2-t_1} = \beta \Delta TPP_{c,t_2-t_1} + \gamma \Delta AES_{c,t_1-t_0} + \theta X_c + \psi_s + \epsilon_c \ (3.5)$$

We utilize county-level agricultural employment share of total working age population data from the Census Bureau. Table 3.3. summarizes the results. Again, rising net trade exposure on U.S. county-level result in an increase in employment share of agricultural-related employment share across the periods between 2012-2017 and 2007-2017. Quantitatively, a \$1,000 increase in net trade exposure per person, leads to a 0.324 percentage point increase in agricultural-related employment share in working age population.

Noticeably, each Chapter use different types of employment-related variables as dependent variable. In Chapter 1, increasing export exposure to China results in increase in hired farm labor numbers. In Chapter 2, increase import exposure to the top 20 suppliers leads to declines in all types of farm workers and producers. Here in Chapter 3, we utilize the agricultural-employment share of working age population and are able to demonstrate that 1) the overall agricultural trade exposure, combining factors from both imports and exports, is positive. 2) in terms of how positive it is, thanks to the modified methodology in Chapter 3, we can directly compare our results with Autor et al. (2013)'s results. In their estimations, between the period of 2000 and 2007, a $1,000 increase in rising import exposure to China leads to a 0.75 percentage point decrease in manufacturing employment share of the working population. In similar 5-year span of 2007 and 2012, we show that agricultural trade achieved opposite results compared with manufacturing.

Political Effects?

Ultimately, the goal of this dissertation is to promote the positive sides of trade using the example of agriculture. And like we introduced in motivation section, one of the major events that contributes to this idea is the trade war episodes between 2018 and 2019. How trade policies can be utilized as instruments to achieve political targets is an important question to answer. Recent years, due to the involvement of tariffs and MFP, economists jumped on this topic trying to explain the role of trade in the context of political economy, especially with an emphasize on Trump administration and its decisions (Blanchard, et al. 2019; Janzen and Hendricks, 2020; and Choi and Lim, 2022).

Intuitively, the initiation of the trade war and its associated MFP directly affect the outcomes of net trade exposure (see the map in Figure 3.2). Benefited from the convenience in already built a net trade exposure structure, we follow Choi and Lim (2022) to investigate how change in net trade exposure affected the change in U.S. county-level Republican Vote shares between 2016 and 2020 U.S. Presidential elections. The model is shown in equation 3.6.

$$\Delta RVS_{c,t_2-t_1} = \beta\Delta TPP_{c,t_2{}',-t_1{}'} + \gamma\Delta RVS_{c,t_1-t_0} + \delta RVS_{c,t_1} + \theta X_c + \psi_s + \epsilon_c \quad (3.6)$$

$\Delta RVS_{c,t_2-t_1}$ is the change in county-level Republican vote share which is between 2016 and 2020 in our case. $\Delta TPP_{c,t_2{}',-t_1{}'}$ is the county-level change in net trade exposure. In the case of 2018 trade war, we utilize the change in net trade exposure between 2017 and 2019 to capture the corresponding changes in trade values. We still control for the previous existing voting trend

$\gamma\Delta RVS_{c,t_1-t_0}$ in the changes of county-level Republican vote share between the 2012 and 2016 U.S. presidential elections. Compared with the previous models in analyzing net farm income and agricultural employment share, the major difference in this model is that it adds another variable $\delta RVS_{c,t_1}$ to control for the county-level Republican vote share in specifically the 2016 election where President Trump won. State-level fixed effects and the previously included control variables are still included as they are effective to control for voting patterns across different characteristics.

Column (1) to (4) from Table 3.4 shows the regression results. Across all these columns, the impacts of net trade exposure result in an increase in Republican vote share. A $1,000 increase in net trade exposure is predicted to increase the county-level Republican vote share by 0.01 percentage points. These results imply that the change in net trade exposure during the trade war periods, which was directly affected by Trump administration's trade policies and its associated consequences, contribute to the achievement of their political targets and result in an increase in county-level voting shares in their favor.

Comparatively, we conducted another falsification assessment to test whether the results pertain during the second term of Obama administration between 2012 and 2016. And unsurprisingly, no such clear effects are detected with same level of controls. During the second term of the Obama administration, changes in trade exposure are not found to be statistically connect with changes in voting shares between the 2012 and 2016 U.S. Presidential elections, further confirming our causality statement that it is the changes in Trump administration's trade policies that led to the increase in vote shares.

Conclusions

Trade, in conventional economic theories were described as Pareto improving. However, accompanied with the rising surge in manufacturing imports from China and the episodes from recent trade war, the effectiveness and resulting consequences of trade have been debatable and controversial over the past decade. Agriculture, staying on the opposite side of U.S. trade balance sheet compared with manufacturing, in addition to its uniqueness in being targeted by foreign retaliatory tariffs, provides a great opportunity to demonstrate the overall positivity of trade. As the U.S. society and some researchers emphasized on the negative side, assessing the effect of U.S. agricultural trade is crucial for our understanding of U.S. domestic outcomes.

Thanks to a sophisticated and peer-reviewed county-level trade exposure construction methodology, we study the effect of U.S. agricultural trade individually on export and import side in Chapter 1 and 2. In this Chapter, we modify this exposure construction method, combining updates from recent literature about agriculture due to the trade war, re-structure the fundamental product aggregation and overcome the data limitations to develop an innovative model that is capable of assessing the net agricultural trade exposure from the year of 1997 to 2017.

Our core findings are as follows. The net trade exposure rates show less variation across U.S. counties compared with export and import exposures. And the trade war deeply challenged the net trade exposure rates. The net trade exposure largely benefits U.S. county-level aggregated net farm income and agricultural employment share of total working age population, across all 5-, 10-, and 15-year periods, contradictory to what has been discovered in the manufacturing industry. The change in net trade exposure during the trade war periods, which was directly affected by Trump administration's trade policies and its associated consequences, contribute to the achievement of their political targets and result in an increase in county-level voting shares in their favor.

Table 3.1. Change in Net Trade Exposure in 10-, and 15-year Intervals and Change of Net Farm Income in U.S. Counties

	ΔNet Farm Income 2002-2012		ΔNet Farm Income 2007-2017			ΔNet Farm Income 2002-2017	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. 2002-2017							
ΔTPP_{0212}	10,702.4***	7,079.1***					
Panel B. 2007-2017							
ΔTPP_{0717}			3,631.4***	4,238.7***	4,019.1***		
ΔTPP_{0207} (Pre-Trend)			-0.295***	-0.280***	-0.302***		
Panel C. 2002-2017							
ΔTPP_{0217}						5,905.2**	4,733.9***
State FEs	No	Yes	No	Yes	Yes	No	Yes
County Controls	No	No	No	No	Yes	No	No
Observations	3,022	3,022	3,002	3,002	3,001	3,021	3,021
R-squared	0.054	0.321	0.125	0.240	0.272	0.037	0.160

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

Table 3.2. Change in Net Trade Exposure in 5-year Intervals and Change of Net Farm Income in U.S. Counties

	ΔNet Farm Income 2002-2007		ΔNet Farm Income 2007-2012			ΔNet Farm Income 2012-2017		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. 2002-2007								
ΔTPP_{0207}	7,673.1***	8,463.6***						
Panel B. 2007-2012								
ΔTPP_{0712}			3,807.0***	2,341.9***	2,079.5***			
ΔTPP_{0207} (Pre-Trend)			-0.117***	-0.224*	-0.240***			
Panel C. 2012-2017								
ΔTPP_{1217}						1,240.6	2,166.9***	1,985.5***
ΔTPP_{0712} (Pre-Trend)						-0.606***	-0.535***	-0.533***
State FEs	No	Yes	No	Yes	Yes	No	Yes	Yes
County Controls	No	No	No	No	Yes	No	No	Yes
Observations	3,010	3,010	3,002	3,002	3,001	3,005	3,005	3,004
R-squared	0.013	0.193	0.018	0.230	0.254	0.337	0.468	0.487

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

Table 3.3. Change in Net Trade Exposure in 5-, and 10-year Intervals and Change of Employment Share in Agriculture in U.S. Counties

	ΔEmployment Share in Agriculture 2007-2012		ΔEmployment Share in Agriculture 2012-2017			ΔEmployment Share in Agriculture 2007-2017	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. 2002-2007							
ΔTPP_{0712} /1000	-0.002	0.058					
Panel B. 2012-2017							
$\Delta TPP_{1217}/1000$			0.250***	0.312***	0.324***		
$\Delta TPP_{0712}/1000$ (Pre-Trend)			-0.447***	-0.462***	-0.456***		
Panel C. 2007-2017							
$\Delta TPP_{0717}/1000$						0.164**	0.227***
State FEs	No	Yes	No	Yes	Yes	No	Yes
County Controls	No	No	No	No	Yes	No	No
Observations	3,066	3,063	3,065	3,065	3,065	3,066	3,066
R-squared	0.000	0.021	0.048	0.074	0.084	0.002	0.033

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

Table 3.4. Change in Aggregated Trade and Change of Republican Vote Shares in 2020 and 2016 U.S. Presidential Elections in U.S. Counties

	ΔRepublican Vote Share 2016-2020				ΔRepublican Vote Share 2012-2016			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. 2016-2020								
ΔTPP_{1719}	0.02***	0.01**	0.01***	0.01**				
ΔRVS_{1216} (Pre-Trend 1)		0.03***	0.21***	0.17***				
RVS_{16} (Pre-Trend 2)		0.01**	-0.03***	-0.07**				
Panel B. 2012-2016								
ΔTPP_{1215}					0.00	0.00	-0.01***	0.00
ΔRVS_{0812} (Pre-Trend 1)						0.22***	0.111***	-0.17***
RVS_{12} (Pre-Trend 2)						-0.05***	0.01	-0.07**
State FE	No	No	Yes	Yes	No	No	Yes	Yes
County Controls	No	No	No	Yes	No	No	No	Yes
Observations	3,069	3,068	3,068	3,068	3,064	3,064	3,064	3,064
R-Squared	0.003	0.009	0.390	0.544	0.000	0.019	0.453	0.695

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

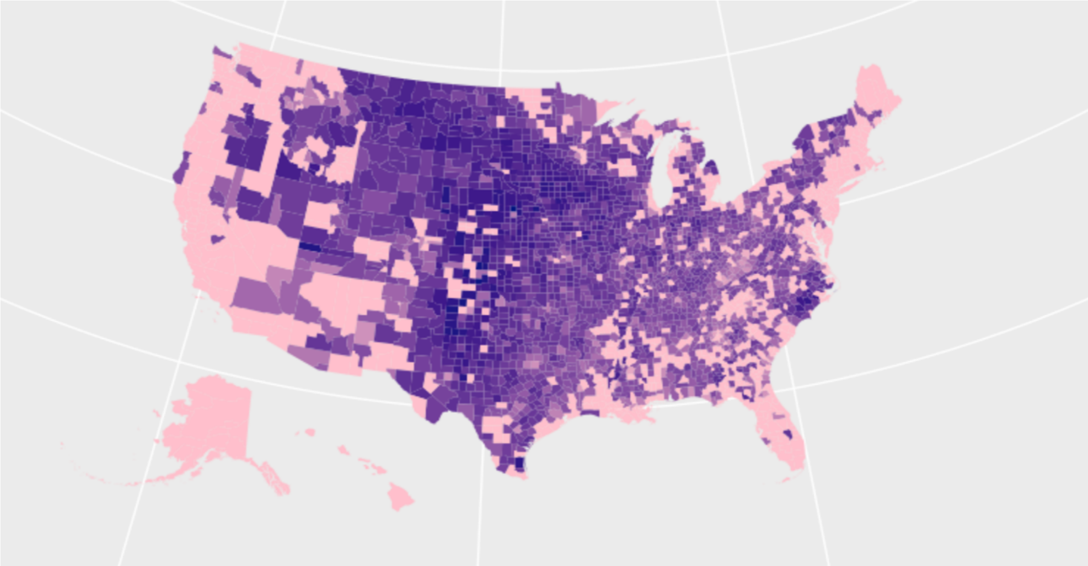

Figure 3.1. U.S. County-Level Net Trade Exposure Rates, 2007-2017[31]

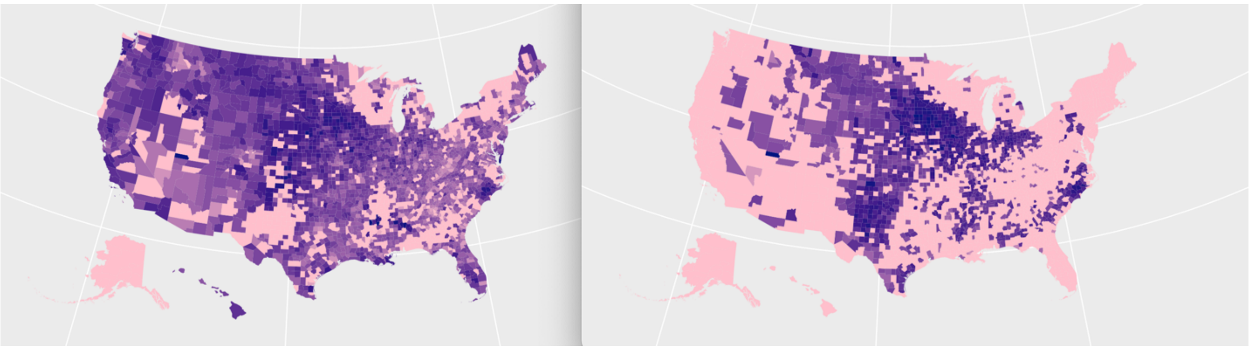

Figure 3.2. U.S. County-Level Net Trade Exposure Rates, 2007-2009, 2017-2019[32]

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[31] Note: Darker colors represent greater levels of exposure.

[32] Note: Darker colors represent greater levels of exposure.

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APPENDICES

A. CROSSWALK ON AGRICULTURAL COMMODITIES BETWEEN U.S. CENSUS DATA AND TRADE DATA[33]

	U.S. Census of Agriculture	FATUS	Harmonized System Codes (2-digit level)
Crop Totals	1. Grain 2. Cotton, Lint and Seed 3. Vegetable Totals 4. Fruit and Tree Nut Totals 5. Berry Totals 6. Horticulture Totals 7. Cut Christmas Trees and Short-Term Woody Crops 8. Field Crops 9. Corn 10. Wheat 11. Soybeans 12. Sorghum 13. Barley 14. Grain, other	1. 2000CT Grains and Feeds 2. 2500CT Fruit and Prep 3. 3290CT Nuts and Prep 4. 4290CT Vegetables and Prep 5. 5000CT Oilseeds and Prods 6. 5750CT Cotton, Ex Linters 7. 6000CT Cotton Linters 8. 6100CT Cotton, Waste 9. 6250CT Essential Oils 10. 6500CT Seeds, Field/Garden 11. 7250CT Other Hort Products 12. 7500CT Nursery and Greenhouse	06 07 08 09 10 11 12 13 14 18 19 20 21 52
Animal Totals	1. Poultry Totals 2. Cattle 3. Milk 4. Hogs 5. Sheep and Goat Totals 6. Equine 7. Aquaculture Totals 8. Specialty Animal Totals	1. 1000CT Animals and Animal Prods 2. 9000CT Fish and Selfish	01 02 03 04 05 15 16 41

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[33] For validation purpose, we cross referenced the aggregated level of export data between FATUS and HS groups for years in 1997, 2002, 2007, 2012, 2017 and 2018. Most of the difference margins are within 5%. See Appendix B for details.

B. CROSSWALK VALIDATION BETWEEN FATUS GROUP AND HS GROUP USING REALIZED DATA

	FATUS	Harmonized System Codes (2-digit level)
Crop Totals	1. 2000CT Grains and Feeds 2. 2500CT Fruit and Prep 3. 3290CT Nuts and Prep 4. 4290CT Vegetables and Prep 5. 5000CT Oilseeds and Prods 6. 5750CT Cotton, Ex Linters 7. 6000CT Cotton Linters 8. 6100CT Cotton, Waste 9. 6250CT Essential Oils 10. 6500CT Seeds, Field/Garden 11. 7250CT Other Hort Products 12. 7500CT Nursery and Greenhouse	06 07 08 09 10 11 12 13 14 18 19 20 21 52
Animal Totals	1. 1000CT Animals and Animal Prods 2. 9000CT Fish and Selfish	01 02 03 04 05 15 16 41

Panel A. Crop Totals

Year	Aggregated Total Export to China (in nominal billion dollars)	Aggregated Total Export to China (in nominal billion dollars)	Difference
1997	1.10	1.35	19%
2002	1.39	1.42	2%
2007	6.06	6.30	4%
2012	21.33	22.43	5%
2017	16.40	16.69	2%
2018	6.57	6.85	4%

Panel B. Animal Totals

Year	Aggregated Total Export to China (in nominal billion dollars)	Aggregated Total Export to China (in nominal billion dollars)	Difference
1997	0.52	0.36	46%
2002	7.75	0.77	0%
2007	2.68	2.46	9%
2012	4.52	4.31	5%
2017	3.69	3.74	1%
2018	3.01	3.08	2%

C. CROSSWALK ON AGRICULTURAL COMMODITIES BETWEEN U.S. CENSUS DATA AND TRADE DATA, CHAPTER 3

	Harmonized System Codes (6-digit level)	U.S. Census of Agriculture
Exports	1. 120190-Soybeans 2. 100590-Corn 3. 100199, 100119-Wheat 4. 080212, …, 080290-Tree Nuts 5. 020230, …, 021020-Beef & Beef Products 6. 520100-Cotton 7. 030499, …, 160562-Seafood Products 8. 020329, …, 020641-Pork & Pork Products 9. 040210, …, 040310-Dairy Products 10. 080810, …, 080840-Fresh Fruit 11. 020714, …, 020751-Poultry Meat & Prods. (ex. eggs) 12. 230400, 120810-Soybean Meal 13. 200410, …, 071233-Processed Vegetables 14. 070519, …, 070952-Fresh Vegetables 15. 200893, …, 200891-Processed Fruit 16. 040711, …, 040790-Eggs & Products	1. & 12. Soybeans 1 2. Corn 2 3. Wheat 3 4. 10. & 15. Fruit & Tree Nut 4 5. Cattle, incl Calves 5 6. Cotton, Lint & Seed 6 7. Aquaculture 7 8. Hogs 8 9. Milk, incl Other Dairy Products 9 11. & 16. Poultry, incl Eggs 10 13. & 14. Vegetable, incl Seeds & Transplants 11
Imports	1. 080110, …, 081440-Fruit 2. 030110, …, 030910-Seafood 3. 070110, …, 071490-Vegetables, Edible 4. 200110, …, 200990-Preparations of Vegetables 5. 040110, …, 040190-Dairy Products 6. 520100-Cotton 7. 020110, …, 020230-Meat; of Bovine Animals 8. 020311, …, 020329-Meat; of Swine	1. Fruit & Tree Nut 2. Aquaculture 3. & 4. Vegetable, incl Seeds & Transplants 5. Milk, incl Other Dairy Products 6. Cotton, Lint & Seed 7. Cattle, incl Calves 8. Hogs

D. SUMMARY STATISTICS OF CONTROL VARIABLES

Panel A. American Community Survey Results, 2010, 5-year Estimates, in %

	Mean	SD	Min	Max
Industry Characteristics				
Employment Share, Agriculture and Mining	6.80	7.43	0.0	52.4
Employment Share, Manufacturing	12.34	7.13	0.0	80.2
Demographic Characteristics				
Population Share, Female	50.10	2.34	23.6	57.5
Population Share, Age under 5	6.24	1.27	0.0	14.9
Population Share, Age 5-9	6.33	1.20	0.0	12.9
Population Share, Age 10-14	6.78	1.19	0.0	17.4
Population Share, Age 15-19	7.23	1.51	0.0	24.8
Population Share, Age 20-24	6.15	2.53	0.0	26.6
Population Share, Age 25-34	11.39	2.33	2.6	36.6
Population Share, Age 35-44	12.85	1.75	4.6	25.4
Population Share, Age 45-54	14.95	1.71	5.4	31.7
Population Share, Age 55-59	6.76	1.24	1.8	24.1
Population Share, Age 60-64	5.81	1.31	0.0	15.4
Population Share, Age 65-74	8.28	2.15	0.0	26.4
Population Share, Age 75-84	5.14	1.70	0.0	23.0
Population Share, Age over 85	2.04	0.97	0.0	9.0
Population Share, White	83.59	16.79	3.3	100.0
Population Share, Black or African	8.86	14.49	0.0	86.1
Population Share, Asian	1.12	2.60	0.0	52.2
Population Share, Hispanic	10.02	18.89	0.0	99.9

Panel B. American Community Survey Results, 2012, 5-year Estimates, in %

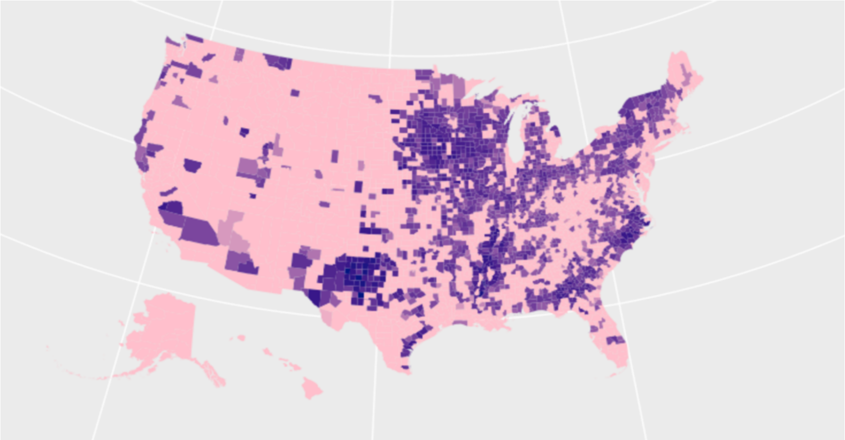
	Mean	SD	Min	Max
Industry Characteristics				
Employment Share, Agriculture and Mining	6.80	7.42	0.0	58.9
Employment Share, Manufacturing	12.17	7.03	0.0	79.1
Demographic Characteristics				
Population Share, Female	50.04	2.38	23.5	57.7
Population Share, Age under 5	6.17	1.24	0.0	12.5
Population Share, Age 5-9	6.34	1.22	0.0	11.6
Population Share, Age 10-14	6.64	1.16	0.0	13.1
Population Share, Age 15-19	6.97	1.36	0.0	20.7
Population Share, Age 20-24	6.18	2.54	0.3	32.5
Population Share, Age 25-34	11.51	2.23	4.0	34.1
Population Share, Age 35-44	12.28	1.69	1.8	23.3
Population Share, Age 45-54	14.73	1.62	4.0	28.2
Population Share, Age 55-59	6.98	1.31	0.9	20.0
Population Share, Age 60-64	6.21	1.33	0.0	16.2
Population Share, Age 65-74	8.73	2.24	2.8	29.0
Population Share, Age 75-84	5.17	1.64	0.0	15.2
Population Share, Age over 85	2.09	0.93	0.0	8.9
Population Share, White	83.65	16.75	3.1	100.0
Population Share, Black or African	8.90	14.42	0.0	86.2
Population Share, Asian	1.15	2.55	0.0	44.1
Population Share, Hispanic	10.49	19.12	0.0	99.9

Panel C. American Community Survey Results, 2017, 5-year Estimates, in %

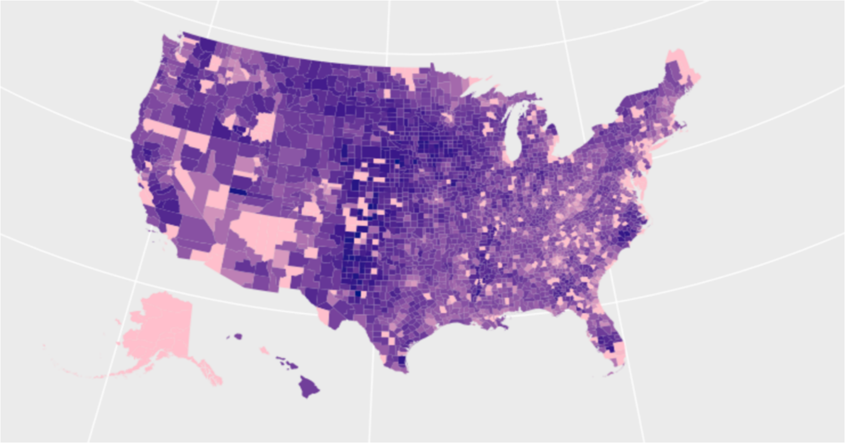
	Mean	SD	Min	Max
Industry Characteristics				
Employment Share, Agriculture and Mining	6.68	7.35	0.0	63.0
Employment Share, Manufacturing	12.26	7.15	0.0	55.1
Demographic Characteristics				
Population Share, Female	49.96	2.42	19.2	58.1
Population Share, Age under 5	5.83	1.21	0.0	12.5
Population Share, Age 5-9	6.26	1.21	0.0	12.9
Population Share, Age 10-14	6.43	1.16	0.0	14.1
Population Share, Age 15-19	6.51	1.39	0.0	26.2
Population Share, Age 20-24	6.36	2.42	0.5	32.1
Population Share, Age 25-34	11.74	2.27	0.0	26.6
Population Share, Age 35-44	11.64	1.54	2.8	20.8
Population Share, Age 45-54	13.25	1.52	4.1	25.3
Population Share, Age 55-59	7.28	1.29	1.9	27.0
Population Share, Age 60-64	6.78	1.37	1.1	17.4
Population Share, Age 65-74	10.23	2.53	1.2	33.7
Population Share, Age 75-84	5.47	1.66	0.9	16.6
Population Share, Age over 85	2.23	0.93	0.0	9.2
Population Share, White	82.85	16.97	4.0	100.0
Population Share, Black or African	9.04	14.46	0.0	86.9
Population Share, Asian	1.31	2.76	0.0	42.9
Population Share, Hispanic	11.30	19.34	0.0	100.0

E. 5-, 10-, AND 15-YEAR PERIOD CHANGE IN TOTAL TRADE EXPOSURE PER PERSON IN U.S. COUNTY-LEVEL MAP

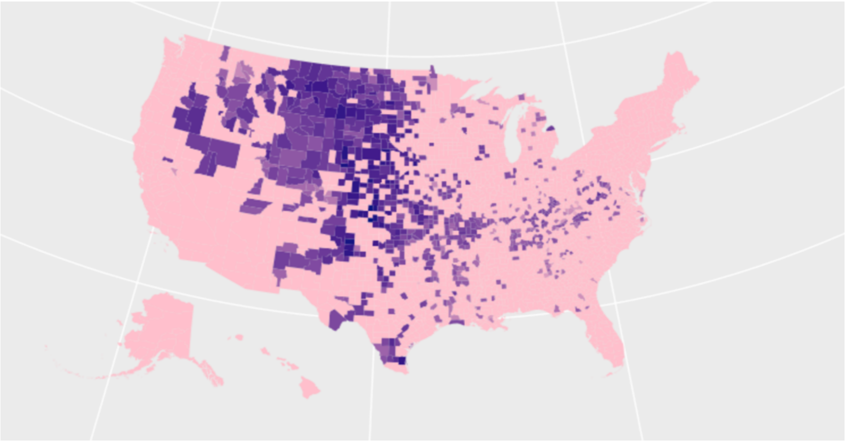
Panel A. 5-Year Period



2002-2007

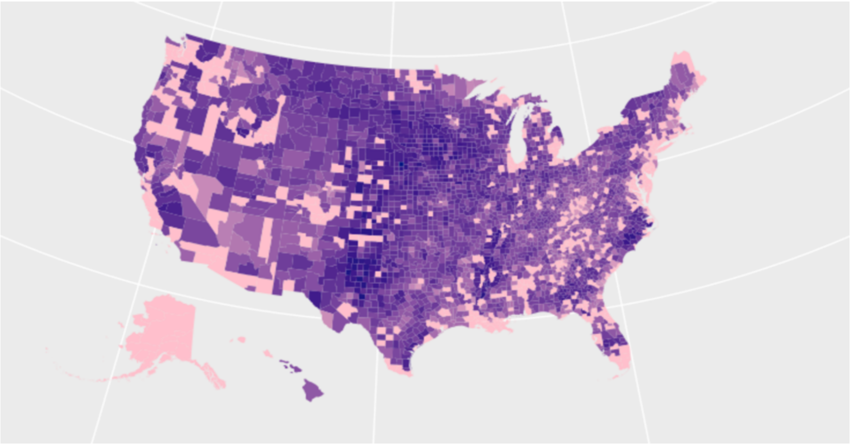


2007-2012

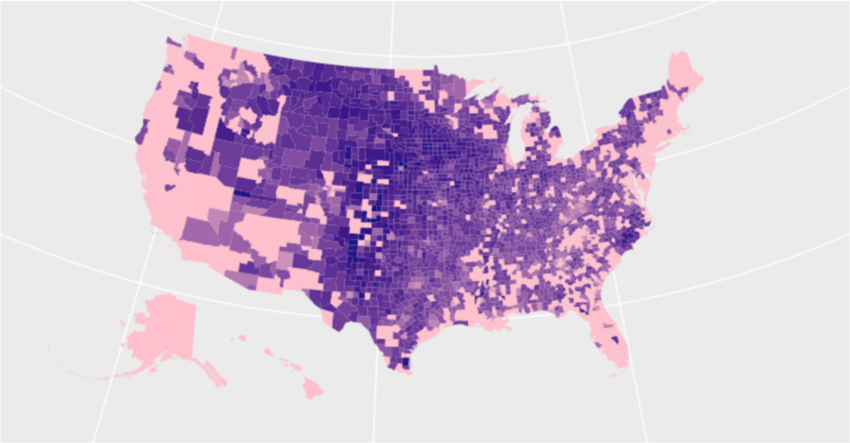


2012-2017

Panel B. 10-Year Period

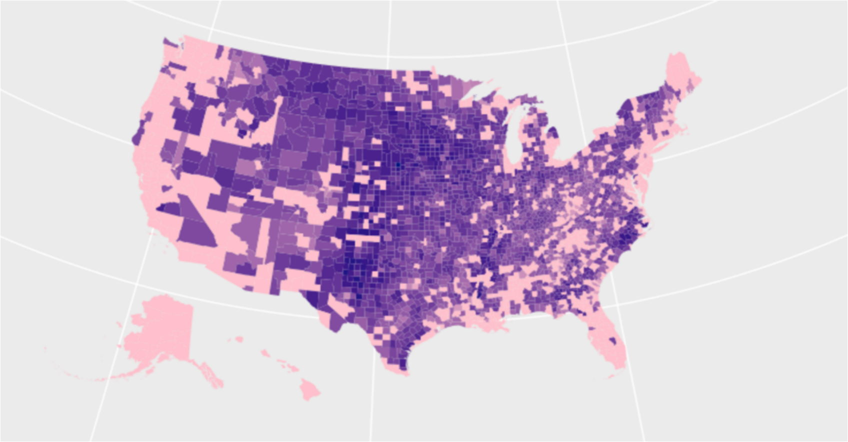


2002-2012



2007-2017

Panel C. 15-Year Period



2002-2017