# Assessing impact of better foreign market accessibility on crop production and farm economy

by

Jiyeon Kim

B.A., Kangwon National University, 2015

M.A., Seoul National University, 2018

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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
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DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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# Abstract

The interplay between international trade and agricultural policy is crucial to understanding current agricultural issues surrounding global agricultural markets. Understanding these dynamics is essential for addressing the challenges and opportunities the agricultural sector faces, which has been increasingly interconnected with international markets. U.S. agriculture has been experiencing increases in imports and exports of agricultural commodities over the last three decades with its trade liberalization. In particular, North American Free Trade Agreement (NAFTA) boosted agricultural trade among the United States, Canada, and Mexico by reducing trade barriers within those three countries.

With better accessibility to foreign markets, U.S. agriculture may gain or lose from trade, and the impact of trade can be heterogeneous across regional or individual agricultural backgrounds. The potential benefits are particularly pronounced for exporters who experience significant reductions in tariffs on products that they produce as a result of trade liberalization. On the other hand, if individual farm operators lose their competitiveness in producing and exporting, it would impact farm business decisions on input use, crop choice, or exit from the market at worst. Hence, it becomes important to understand the impact of trade exposure on agricultural production and farm economy with a keen focus on identifying the heterogeneous effects across regions or individuals.

The first study examines how U.S. crop acreage and yield respond to better foreign market accessibility caused by NAFTA focusing on the heterogeneous effects across regions with different export competitiveness and agricultural backgrounds. Focusing on the major field crops, corn, soybeans, and wheat, we compute the localized trade exposure and examine the effect of localized trade exposure on U.S. crop acreage and yield. Using a comprehensive dataset on crop production and bilateral trade data from 1991 to 2022, and localized trade exposure, we find that trade shocks from NAFTA have negative impacts on crop acreages

but positive impacts on crop yield for corn and soybeans. In addition, the effects are heterogeneous by crops and different stages of NAFTA implementations.

The second study estimates how the farm-level trade exposures from NAFTA affect the profitability of farms and, as a result, how changes in the profitability after the implementation of NAFTA impact the survival of farms. We estimate the effects of trade exposure on farm profit using a farm-level panel data and trade data from 1991 to 2022. We also employ a duration model to investigate the effects of trade exposure on farm exit. The findings of this study are mixed depending on how trade exposure is measured. When trade exposure is quantified by the U.S. revealed comparative advantage (RCA) in exports, trade exposure is positively associated with farm profitability and the likelihood of farm survival. However, when trade exposure is measured by the U.S. market share in NAFTA countries, the results suggest a positive impact of trade exposure on profitability, but a negative association between trade exposure and farm survival.

The third study investigates effects of a free trade agreement from an importing country's perspective. Using farm-level panel data and bilateral trade data from 2003 to 2007, we directly estimate the impacts of the Korea-Chile Free Trade Agreements (FTA) on the revenue of farms in South Korea that faced greater imports – agricultural producers as the FTA induced greater imports of fruits and vegetables from Chile to South Korea. As expected, we find the negative effect of the increased imports on the total crop revenue and profit of the farms. We model and examine the differential impacts and find that the negative effects are greater for high-revenue farms. We document the evidence on the lack of immediate adjustment as a response to the negative shocks from the trade agreement.

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# Chapter 1

# Introduction

This dissertation explores the economic implications of trade policies on agricultural production and farm economy at both regional and individual levels. Particularly, the focus is on how the changes in the trade environment influence production decisions, profitability, and farm survival.

Chapter 2 uses U.S. county-level aggregate data to explore how the greater export exposure caused by North American Free Trade Agreement (NAFTA) influences production decisions. The outcomes of interest are crop acreage and yield, which are the results of production decisions by farms. We compute the localized trade exposure and examine the effect of localized trade exposure on U.S. crop acreage and yield. Using a comprehensive dataset of U.S. county-level crop production and bilateral trade data from 1991 to 2022, we find that trade shocks from NAFTA have negative impacts on crop acreages for corn and soybeans on average, and positive impacts on crop yield for corn and soybeans. The finding of the study shows the complexity of production responses to the changes in the trade environment.

Chapter 3 examines the effect of trade exposure at the individual-level focusing on farms in Kansas. Specifically, we quantify the farm-level trade exposure and study how the greater trade exposure due to NAFTA affects farm profitability and, as a result, influences the survival of farms through changes in profitability. With a comprehensive dataset of farm-level production and bilateral trade data from 1991 to 2022, we find that the greater trade exposure of farms is positively associated with farm profit and the probability of farm survival when U.S. revealed comparative advantage increases. The findings suggest that accessibility to foreign markets plays a significant role in the farm economy and the long-term viability of farm business. This highlights the importance of policies and strategies that improve foreign market access, particularly in the context of global trade dynamics in agriculture.

Individual farms that lose their competitiveness in the domestic market due to the greater imports respond to the trade shock differently. Focusing on South Korea's agricultural imports from Chile, Chapter 4 investigates how Korea-Chile Free Trade Agreement (FTA) affects the farms in Korea. The outcomes we considered are the total crop revenue and profit of farms. Using farm-level production data and bilateral trade data from 2003 to 2007, we compute farm-level import exposure and estimate the effect of Korea-Chile FTA on total crop revenue and profit of the farms. We find negative impacts, in particular greater negative impacts for high-revenue farms. The finding of the study documents that the lack of immediate adjustment plays a significant role in mitigating the negative shocks in the immediate- or short-term.

# Chapter 2

# Effects of North American Free Trade Agreement on the U.S. crop acreage

## 2.1 Introduction

Better accessibility to foreign markets provides opportunities for U.S. agricultural producers to gain from trade. Gains may come from changes in the relative price of crops due to increases in foreign market demand. This may affect crop supply by changing producers' expectations of the profitability for crops that experienced greater relief from trade barriers, resulting in increasing acreage of crops that have faced more tariff reductions or better market accessibility.

The objective of this study is to estimate U.S. crop acreage responses to better foreign market accessibility caused by the North American Free Trade Agreement (NAFTA) focusing on the heterogeneous effects across regions with different levels of competitiveness in their production. We examine how changes in the U.S. comparative advantage in major crop exports after the implementation of NAFTA impacted crop acreage in the U.S. and how crop acreages responded differently across regions with different crop production patterns. To do so, we build our empirical strategy based on the shift-share design combined with various panel approaches.

In this study, we study NAFTA for a couple of reasons. First, Canada and Mexico are major agricultural trade partners of the U.S. Second, since NAFTA has been enforced, the agreement reduced almost all barriers to trade and investment among those three countries, resulting in increases in the size of U.S. agricultural trade with members of NAFTA.

We relate our study to two streams of literature. First is the group of studies that take partial or general equilibrium simulation-based approaches to assess trade impacts on input market or output price. With the increasing trade in low-wage countries, such as China, many economists provide empirical evidence on the negative effect of import shocks from China on the local labor markets in the U.S. (e.g., Acemoglu et al., 2016; Autor et al., 2013; Feenstra and Sasahara, 2018; Costa et al., 2016) and Brazil (e.g., Dix-Carneiro and Kovak, 2017).

While these studies focus on the manufacturing sector, many studies in agriculture explore the impact of retaliatory tariffs on export value or crop prices (Carter and Steinbach, 2020; Grant et al., 2021; Adjemian et al., 2021), but these results only provide short-run implications for the tariffs. In terms of market access, He (2020) and Yu et al. (2022) examine the effects of changes in access to foreign markets on U.S. agriculture. He (2020) analyzes how "China shock" impacts U.S. labor markets and finds that increased imports from China negatively affect farm employment. Yu et al. (2022) estimates the effects of localized tariff exposure on farmland rental rate using measures of localized tariff reductions. They show that the U.S. farmland rents increased as the localized tariff decreased. Despite the direct empirical estimates of the effect of changes in localized tariff exposure, it is relatively unknown how improved foreign market accessibility affects crop supply and producers across different regions, especially considering that regions have different production capacities and agricultural backgrounds may respond differently to enhanced foreign market accessibility.

This study also relates to the recent literature on crop supply analysis. There are many studies that examine crop acreages response to climate change (e.g., Miao et al., 2016; Arora et al., 2020; Burke and Emerick, 2016), changes in demand for biofuel (e.g., Roberts and Schlenker, 2013; Li et al., 2019; Kim and Moschini, 2018), and international crop price (e.g., Haile et al., 2014, 2016). Mostly, researchers have paid attention to the effects of price and weather patterns on crop supply, taking into account the price expectations of producers (e.g., Haile et al., 2014; Hendricks et al., 2014; Li et al., 2019; Miao et al., 2016; Pates and Hendricks, 2021). Previous studies have endeavored to elucidate farmers' expectations of price by employing various price proxies to represent their anticipations of price (e.g., Gardner, 1976; Haile et al., 2014; Hendricks et al., 2015; Li et al., 2019; Miao et al., 2016; Nerlove, 1956; Roberts and Schlenker, 2013).

We contribute to the literature by providing direct estimates of the crop acreage and yield responses to trade shock from NAFTA, highlighting the regional heterogeneity in the effects of NAFTA on crop supply. In particular, unlike previous studies on the indirect effects of trade shock on aggregated crop production, we examine the heterogeneous effect of NAFTA by crop by measuring crop-by-region specific trade shock due to NAFTA and exploring the extent of differential impacts by crop and lengths of trade shock. Our findings provide significant implications for understanding regional differences in crop acreage and yield growth.

## 2.2 Data and variables

We construct a county-level dataset including information on crop production, weather, and localized trade exposure. We combine data from the World Integrated Trade Solution (WITS) database (World Bank, 2024), the Food and Agriculture Organization (FAO) of the United Nations database (FAOSTAT, 2024), the U.S. Department of Agriculture (USDA)'s National Agricultural Statistics Service (NASS) and the Census of Agriculture (USDA NASS, 2024). We use data on corn, soybeans, and wheat for the period of 1991-2022.

### 2.2.1 Production, trade, and weather data

This study hypothesizes that the U.S. crop producers' competitiveness in producing and exporting field crops influences crop acreage and yield for those crops. We also hypothesize that the degree to which those crops respond depends on the importance of that crop to a county. Therefore, we measure the importance of the crop to the county by computing the crop share within a county as the planted acreage over cropland from corresponding rounds of the Census of Agriculture.

We use annual county-level survey data from the USDA NASS on planted acreage and yield for major field crops. We focus on the production of corn, wheat, and soybeans in the U.S. from 1991 to 2022. The county-level share of each crop is computed as the crop acreage divided by total cropland acres from the two rounds of the Census of Agriculture. Some crop shares are greater than one because there can be a mismatch between the Census and the survey data. We replace such shares greater than one with one.

Trade data is obtained from UN Commodity Trade (UN Comtrade) using the WITS database. We extract the exporter-importer pair from 1991 to 2022 for all countries and all goods using 6-digit Harmonized Tariff Schedule (HS) codes. Next, we group trade values into commodity categories based on the concordance code provided by the USDA Foreign Agricultural Service (FAS) Global Agricultural Trade System (GATS).[1]

To compute the farm-level trade exposure from NAFTA, we first consider two different measures of the U.S. export competitiveness; one is the revealed comparative advantage (RCA), and the other is U.S. market share in NAFTA partner countries. The RCA, suggested by Balassa (1965), is a measure of a country's comparative advantage in producing and exporting a good relative to total world exports of that good. We define U.S. RCA in exporting crop $j$ as U.S. share of world exports for crop $j$ over the U.S. share of total world exports in all goods. The RCA is calculated using bilateral export data as follows:

$$RCA_{jt}^{U.S.} = \frac{\frac{export_{jt}^{U.S.}}{export_{jt}^{WLD}}}{\sum_{k}^{N}(\frac{export_{kt}^{U.S.}}{export_{kt}^{WLD}})} \tag{2.1}$$

where $export_{jt}^{U.S.}$ is the U.S. exports of crop $j$ to the world including Canada and Mexico, and $export_{jt}^{WLD}$ is the total exports of crop $j$ from all countries to the world. The numerator

[1]To group 6-digit HS codes into categories for major field crops, we use 100590 for corn; 120100, 120190 for soybeans; 100110, 100119, 100190, 100199 for wheat. The definitions of product group can be downloaded from USDA FAS (2024).

of RCA is the U.S. share of world trade in crop $j$, and the denominator is the U.S. share of total exports in all goods $k \in \{1, 2, \ldots, N\}$. If RCA is greater than 1, it indicates that the U.S. has a revealed comparative advantage in the production and export of that good. The higher the value of the U.S. RCA for crop $j$ indicates a stronger export advantage in that crop.

Another measure of the export competitiveness of the U.S. is the U.S. market share in NAFTA countries, which is defined as a ratio of the U.S. export volume over the consumption volume of crop $j$ in NAFTA partners.

$$U.S.\ market\ share = \frac{export_{jt}^{U.S.-NAFTA}}{consumption_{jt}^{NAFTA}} \tag{2.2}$$

where $export_{jt}^{U.S.-NAFTA}$ is the export volume of the U.S. for crop $j$ to Canada and Mexico and $consumption_{jt}^{NAFTA}$ is the consumption volume of crop $j$ in Canada and Mexico, which is calculated for crop $j$ as NAFTA countries' production minus total exports plus total imports. Data on the U.S. export quantity is from USDA FAS, and data on crop consumption is from FAO Food and Agriculture database.

We also utilize information on weather obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) and compute the growing degree days (GDDs) and the heating degree days (HDDs) following Schlenker and Roberts (2009). The temperature thresholds for GDDs are 10°C and 30°C and 30°C for HDDs. Cumulative precipitation during the production periods (April to September) is measured in millimeters. All weather variables are computed using daily data from April to September.

Figure 2.1 presents distributions of the U.S. crop acreage by major field crops from 1991 to 2022. Each color represents the planted acreage for different crops: blue for corn, red for soybeans, and green for wheat. Corn acreage and soybeans acreage have grown gradually over time; in particular, soybeans have shown noticeable growth in its planting area in recent years. On the other hand, wheat acreage shows more stable growth compared to the other two crops, without significant upward or downward trend over 32 years. Overall, the figure shows that the dispersion of crop acreage increases for both corn and soybeans, which may be driven by shifts in market demand, export patterns, or crop rotation practices.

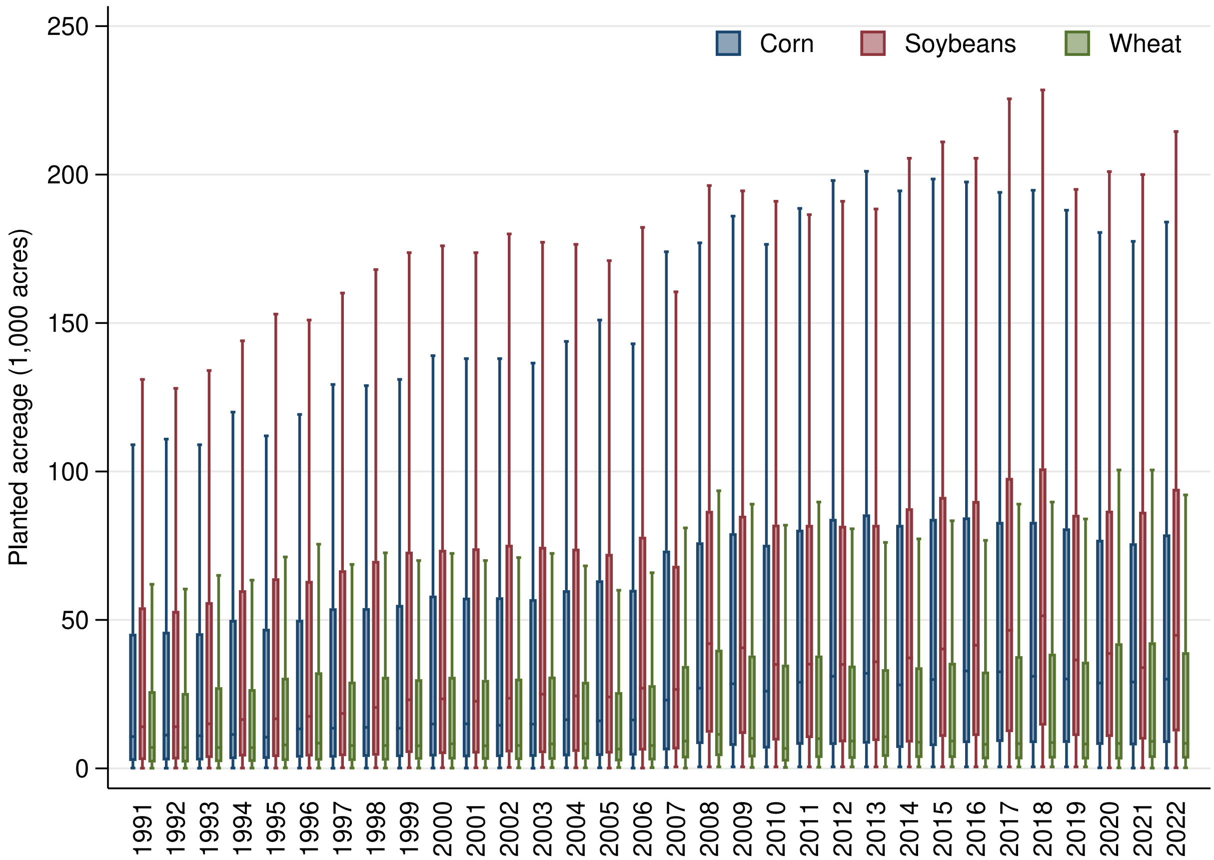


Figure 2.1: Boxplots of crop acreage (1991-2022)

Table 2.1 presents descriptive statistics of all 155,723 county-crop-year combinations across the entire study period, as well as subsets for the first and last three years of the dataset. The overall average planted acres and yield in a county are about 42,180 acres and 76 bushels per acre, respectively. Soybeans represent the largest share among the three field crops, accounting for about 25% of total cropland within the sample counties. Following the soybeans, corn accounts for about 22% of total cropland within the sample counties. The average localized trade exposure measured by RCA and U.S. market share in Canada and Mexico are about 0.12 and 0.03, respectively, for overall periods and the average of both localized trade exposure variables in a county increase over time.

Figure 2.2 shows the trends in the U.S. RCA, computed using equation 3.1, for corn, soybeans, and wheat from 1991 to 2022. Each crop is represented by different colors: blue

Table 2.1: Descriptive statistics of county-crop observations by year

| | (1) Overall | (2) 1991-1993 | (3) 2020-2022 |
|---|---|---|---|
| Planted acres (1,000 acres) | 42.18 | 33.46 | 49.34 |
| | (57.75) | (54.34) | (58.82) |
| Yield (bu/acre) | 75.93 | 60.92 | 94.64 |
| | (49.13) | (38.25) | (58.37) |
| Share of corn (%) | 22.38 | 18.12 | 26.49 |
| | (17.50) | (16.43) | (16.81) |
| Share of soybeans (%) | 25.23 | 19.42 | 30.53 |
| | (17.06) | (16.49) | (16.62) |
| Share of wheat (%) | 13.30 | 12.52 | 13.50 |
| | (15.01) | (15.01) | (14.94) |
| RCA × initial crop share | 0.12 | -0.00 | 0.10 |
| | (0.24) | (0.05) | (0.21) |
| US market share × initial crop share | 0.03 | -0.00 | 0.06 |
| | (0.03) | (0.00) | (0.06) |
| Growing degree days (GDD) (10-30°C) | 1,888.47 | 1,836.83 | 1,877.71 |
| | (464.74) | (488.60) | (397.82) |
| Heating degree days (HDD) (>30°C) | 40.50 | 35.12 | 36.20 |
| | (48.32) | (39.70) | (47.05) |
| Precipitation (mm) | 594.06 | 583.03 | 497.76 |
| | (226.79) | (204.07) | (176.69) |
| Num. of county-crop combinations | 155,723 | 18,500 | 11,836 |

for corn, red for soybeans, and green for wheat. Overall, the U.S. revealed comparative advantages in exporting all three field crops, are greater than one. While all three crops experienced fluctuations in export competitiveness, corn experienced significant spikes in 1995, 2004-2008, and 2018. The U.S. RCA in exporting soybeans shows an upward trend from 1997 to 2009, while the trend gradually turned downward after 2009 to recent years. Notable shifts happened during the early 2000s for corn, with a sharp rise in RCA in 2004 and sharp declines in 2009-2013. The sharp decrease in RCA for corn can be explained by a high domestic demand for corn as ethanol production increased substantially in 2001-2010 (USDA ERS, 2024). Compared to corn and soybeans, wheat maintains a relatively stable

RCA, with a peak in 2004 and a gradual decrease after that.


Figure 2.2: The United States revealed comparative advantage (1991-2022)

### 2.2.2 Localized trade exposure

The main explanatory variable is localized trade exposure, which measures the production impact of NAFTA by crop and the U.S. county. The key challenge is to construct a county-by-crop level shock variable using national-level export data. To do so, we assume that U.S. farms have benefited (or lost) from NAFTA due to the changes in their export competitiveness and the changes affect farms' crop production decisions. We consider two different measures of the U.S. export competitiveness; one is the revealed comparative advantage (RCA), and the other is the U.S. market share in Canada and Mexico. With two different measures of trade, we then convert these national trade measures into county-level shocks based on the share of crop acreage over total cropland, which helps to localize the effects of national trade shocks based on the significance of that crop in each county.

Since the calculations for RCA and the U.S. market share rely on the annual trade and consumption values of Canada and Mexico, some may raise concerns regarding the endogeneity issues. These concerns arise from the fact that annual production influences exports and vice versa. Thus, this study utilizes "shift-share" specifications, motivated by literature (e.g., Bartik, 1991; Autor et al., 2013). Shift-share instruments for localized trade exposure are the weighted averages of trade exposure with weights reflecting heterogeneous shock exposure across regions. This localized exposure is constructed from shocks to crop sectors with local crop acreage shares measuring the shock exposure. Since we assume that the U.S. export competitiveness has been changed after the implementation of NAFTA, we define the pre-NAFTA periods (1991-1993) as the "base period" and compute the annual trade shocks based on such definition to capture the effects of trade shock after implementation of NAFTA.

We calculate the localized trade exposure for county $i$, crop $j$, and year $t \in [1994, 2022]$ as follows:

$$RCA \times crop\ share_{ijt} = (RCA_{jt}^{U.S.} - RCA_{j0}^{U.S.}) \times \frac{A_{ij0}}{Cropland_{i0}} \tag{2.3}$$

and

$$U.S.\ market\ share \times crop\ share_{ijt} = (U.S.\ market\ share_{jt} - U.S.\ market\ share_{j0}) \times \frac{A_{ij0}}{Cropland_{i0}} \tag{2.4}$$

where subscripts $j$ indicates crop, $i$ is county, $t$ is year, and the subscript 0 indicates the 3-year average in 1991-1993. $RCA_{jt}^{U.S.}$ is the U.S. revealed comparative advantage defined in equation 2.1, $U.S.\ market\ share_{jt}$ is the U.S. market share in NAFTA countries, defined in equation 2.2, and $\frac{A_{ij0}}{Cropland_{i0}}$ is an initial crop share, which is defined as the 3-year average of planted acreage over cropland for county $i$ and crop $j$ in 1991-1993.

Figures 2.3 shows boxplots of the localized trade exposure, computed using equations 2.3 and 2.4, for the overall samples to illustrate the annual distributions of localized trade exposure across counties and crops by the two different measures.[2] The left figure illustrates

[2] Boxplots of the localized trade exposure by crop are provided in Appendix A.

the distributions of localized trade exposure measured by RCA. The figure of RCA base localized trade exposure shows that some counties experienced negative trade shocks from 1994 to 2001 and from 2012 to recent years. The right figure presents the distributions of localized trade exposure measured by the U.S. market share in Canada and Mexico. The figure of the U.S. market share base localized trade exposure shows that the gaps in trade exposure across counties and crops gradually increased in 1994-2002, while the variations look steady after 2002 except for the year 2021. Overall, both localized trade exposure variables show huge variations over the entire study period. This suggests that not considering the heterogeneity of trade across regions may overly generalize the results and, as a result, mismeasure the impact of trade.

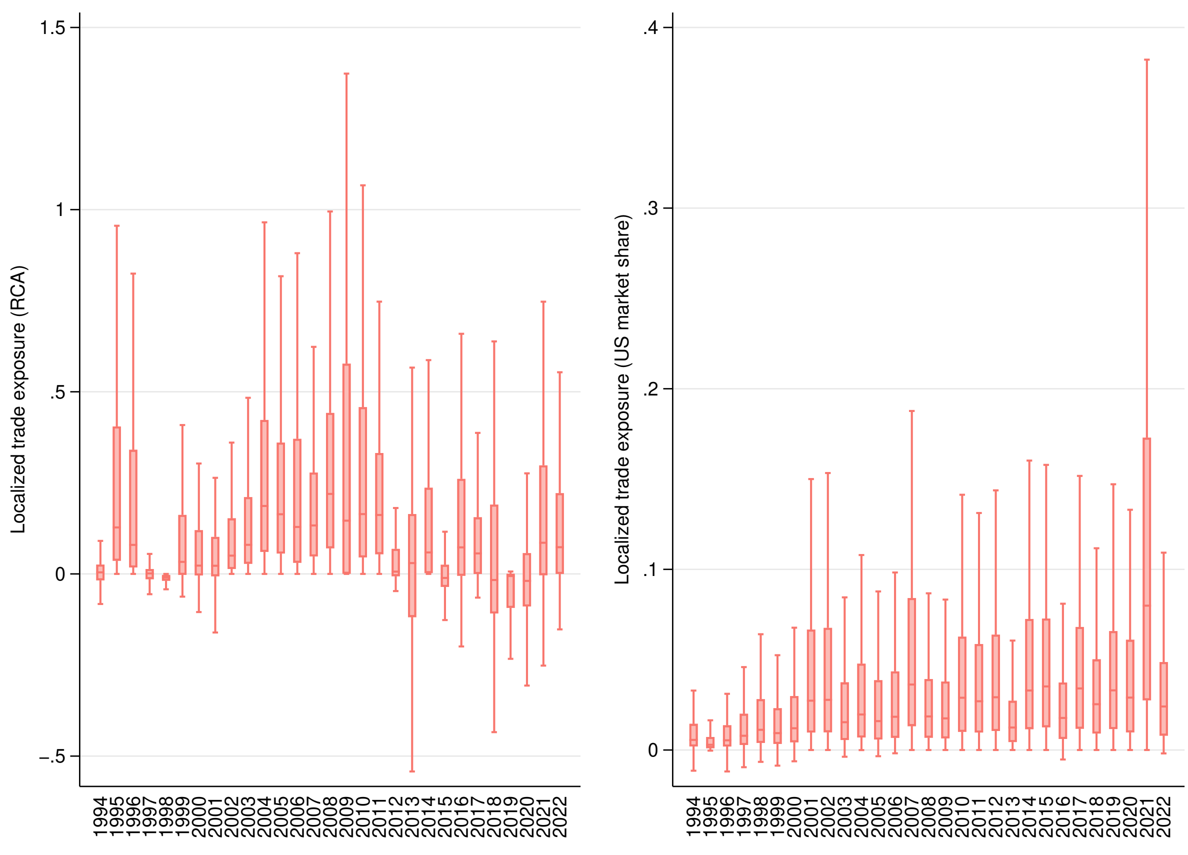


Figure 2.3: Boxplots of localized trade exposure (1994-2022)

## 2.3 Empirical framework

### 2.3.1 Panel fixed effects model

We specify the reduced form of crop acreage and yield model as follows:

$$y_{ijt} = \alpha_1 Trade_{ijt} + \alpha_2 Trade_{ij't} + \alpha_3 Trade_{ij''t} + \Theta X_{it} + u_{ij} + e_t + \epsilon_{ijt} \tag{2.5}$$

Here, the dependent variables, $y_{ijt} \in \{planted\ acres,\ yield\}$, are the level of planted acreage and crop yield for county $i$, crop $j$, and year $t$. The main explanatory variable, $Trade_{ijt}$[3], is the localized trade exposure which is defined in equations 2.3-2.4. We separately estimate the model using those two different localized trade exposure variables. $X_{it}$ is the vector of control variables which includes GDD, HDD, cumulative precipitation during the production periods (April to September), and its squared terms. We also consider trade exposure for each crop's competing crops $j'$ and $j''$ as control variables.[4] To capture unobserved heterogeneity across counties for each crop, the county-crop fixed effect ($u_{ij}$) is included. $e_t$ and $\epsilon_{ijt}$ are year fixed effect and error terms, respectively.

### 2.3.2 First-difference model

To examine the differential impacts of NAFTA on crop acreage and yield response by years, we regress the change in the dependent variable on localized trade exposure for each year in the post-NAFTA period. The estimation model is:

$$\Delta y_{ijt} = \gamma_{1t} Trade_{ijt} + \gamma_{2t} Trade_{ij't} + \gamma_{3t} Trade_{ij''t} + \Gamma \Delta X_{it} + u_s + \epsilon_{ijt} \tag{2.6}$$

where $\Delta$ indicates the difference in the variable from the pre-NAFTA period to year $t$ and all variables are the same as those in equation 2.5. The coefficient that we are interested in is $\gamma_{1t}$ which represents the effects of trade shock on outcomes for year $t$.

[3] $Trade_{ijt} \in \{RCA \times crop\ share_{ijt},\ U.S.\ market\ share \times crop\ share_{ijt}\}$

[4] Yu et al. (2018) show that the competing crops play some roles in crop acreage decision.

### 2.3.3 Long difference model

Since trade restrictions, such as tariffs, had been relieved gradually for some agricultural commodities, we define the pre-NAFTA periods of years 1991-1993 as "base period" and compute the serial trade shocks by taking difference from base period to different stages of transition in post-NAFTA periods (1994-2022) to capture the series effects of NAFTA. To examine the short-run, medium-run, and long-run responses of crop acreage and yield to better foreign market accessibility, we consider the panel long difference (Panel LD) approach. Motivated by Burke and Emerick (2016), we compute the long difference from the 3-year average of variables for the pre-NAFTA (1991-1993) to the 3-year average of variables for 3-year intervals in the post-NAFTA period, $postNAFTA \in \{1994-1996, 1997-1999, 2000-2002, 2020-2022\}$. The estimation equation is:

$$L.y_{ij} = \beta_0 + \beta_1 L.Trade_{ij} + \beta_2 L.Trade_{ij'} + \beta_3 L.Trade_{ij''} + \Gamma L.X_i + u_s + \epsilon_{ij} \tag{2.7}$$

where $L.$ indicates the long difference from the pre-NAFTA (1991-1993) to the post-NAFTA year set and

$$L.Trade_{ij} = (Trade\ measure_{jpostNAFTA} - Trade\ measure_{j0}) \times \frac{A_{ij0}}{Cropland_{i0}}$$

$Trade\ measure$ includes the U.S. export competitiveness measured by RCA and market share. The trade shocks for the competing crops are denoted by subscripts $j'$ and $j''$. We also take the 3-year averages of control variables ($X_i$) and include state-level fixed effects, $u_s$, to account for state-specific policies that might commonly affect crop acreage and yield for all counties in the same state. We estimate the equation 2.7 separately for each 3-year interval $postNAFTA \in \{1994 - 1996, 1997 - 1999, 2000 - 2002, 2020 - 2022\}$. The key coefficient that we are interested in is $\beta_1$, which indicates the cumulative effects of NAFTA on crop acreage from the pre-NAFTA period to each stage of implementing NAFTA.

## 2.4 Estimation results

### 2.4.1 Panel fixed effects model results

Tables 2.2 and 2.3 provide the results from estimating the effects of localized trade exposure on crop acreage and yield by crop. Columns (1), (3), and (5) report the estimation results with localized trade exposure measured by RCA, while columns (2), (4), and (6) report the results with localized trade exposure measured by the U.S. market share.

**Effects of localized trade exposure on crop acreage**

Table 2.2 shows the results from estimating the effects of localized trade exposure on crop acreage by crop. For corn in columns (1)-(2), the estimated coefficient of RCA base trade exposure, -1.829, implies that a county that faced a level of decline in RCA in exporting corn experienced an increase in corn acreage by about 1,829 acres on average. The estimated coefficient of market share base trade exposure, -18.256, indicates that a county that faced a level of decline in the U.S. market share in Canada and Mexico experienced an increase in corn acreage by about 18,256 acres.

For soybeans in columns (3)-(4), we find that both trade exposure variables have a negative impact on soybean acreage. The estimated coefficient of RCA base trade exposure, -2.485, implies that a county that faced a level of decline in RCA in exporting corn experienced an increase in corn acreage by about 2,485 acres. The estimated coefficient of market share base trade exposure, -146.658, indicates that a county that faced a level of decline in the U.S. market share experienced an increase in soybean acreage by about 147 thousand acres.

On the other hand, for wheat in columns (5)-(6), we observe that a county that faced a level of increase in RCA in exporting wheat experienced an increase in wheat acreage by about 8,261 acres on average. The estimated coefficient of market share base trade exposure, -221.148, indicates that a county that faced a level of decline in the U.S. market share experienced an increase in wheat acreage by about 221 thousand acres.

Table 2.2: Effects of localized trade exposure on crop acreage by crop

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Corn | | Soybeans | | Wheat | |
| $Trade_{ijt}$ (RCA) | -1.829*** | | -2.485*** | | 8.261*** | |
| | (0.193) | | (0.367) | | (1.441) | |
| Competing crop 1 | 3.991*** | | 1.786*** | | 0.386*** | |
| | (0.274) | | (0.198) | | (0.147) | |
| Competing crop 2 | -2.522*** | | -22.580*** | | -1.348*** | |
| | (0.977) | | (2.395) | | (0.283) | |
| $Trade_{ijt}$ (U.S. market share) | | -18.256*** | | -146.658*** | | -221.148*** |
| | | (5.080) | | (10.878) | | (12.840) |
| Competing crop 1 | | 29.078*** | | 92.303*** | | 17.918*** |
| | | (6.538) | | (6.748) | | (5.359) |
| Competing crop 2 | | 152.905*** | | 278.810*** | | 3.713 |
| | | (13.605) | | (26.862) | | (7.264) |
| Observations | 51,673 | 51,673 | 42,894 | 42,894 | 42,578 | 42,578 |

Note: The dependent variable is crop acreage (1,000 acres). Weather variables and state fixed effect are included. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

#### Effects of localized trade exposure on crop yield

Table 2.3 shows the results from estimating the effects of localized trade exposure on crop yield by crop. We observe that localized trade exposure positively influences crop yield, except for the results for wheat trade exposure measured by U.S. market share. For corn in columns (1)-(2), the estimated effects of localized trade exposure on corn yield range from 3.220 to 194.185 bushels per acre for counties experiencing increases in export competitiveness.

Similar to results for corn, we find that an increase in export competitiveness has positive impacts on soybean yield ranging from 1.366 to 51.664 bushels per acre and the results are statistically significant. On the other hand, for wheat in columns (5)-(6), we observe that a county that faced a level of increase in RCA in exporting wheat experienced an increase in wheat yield by about 1.3 bushels per acre. However, the estimated coefficient of trade exposure measured by U.S. market share, -34.4, indicates that a county that faced a level of decline in the U.S. market share experienced an increase in wheat yield by about 34.4 bushels per acre.

Table 2.3: Effects of localized trade exposure on crop yield by crop

| VARIABLES | (1) Corn | (2) | (3) Soybeans | (4) | (5) Wheat | (6) |
|---|---|---|---|---|---|---|
| $Trade_{ijt}$ (RCA) | 3.220*** | | 1.366*** | | 1.289 | |
| | (0.260) | | (0.176) | | (1.131) | |
| Competing crop 1 | -7.295*** | | -0.765*** | | 1.523*** | |
| | (0.741) | | (0.077) | | (0.234) | |
| Competing crop 2 | -13.476*** | | -7.954*** | | -7.271*** | |
| | (1.411) | | (0.587) | | (0.417) | |
| $Trade_{ijt}$ (U.S. market share) | | 194.185*** | | 51.664*** | | -34.427*** |
| | | (7.427) | | (2.876) | | (5.417) |
| Competing crop 1 | | 115.432*** | | 37.032*** | | 54.111*** |
| | | (9.290) | | (2.338) | | (4.413) |
| Competing crop 2 | | 91.970*** | | 7.282** | | 51.191*** |
| | | (10.095) | | (3.080) | | (4.381) |
| Observations | 51,371 | 51,371 | 42,893 | 42,893 | 42,529 | 42,529 |

Note: The dependent variable is crop yield (bu./acre). Weather variables and state fixed effect are included. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

### 2.4.2 First-difference model results

Figures 2.4 and 2.5 show the estimated coefficients of equation 2.6 by year using the change in all variables including dependent and control variables. The first row and the second row in figures 2.4-2.5 show the results with trade shock based on the U.S. RCA and market share, respectively. In figures 2.4-2.5, the first column focuses on corn, the second column on soybeans, and the third column on wheat.

#### Effects of trade shocks on crop acreage

Figure 2.4 presents the estimated effects of trade shocks on the change in crop acreage from pre-NAFTA period to each post-NAFTA year. In the results with trade shocks based on RCA, we find that trade shocks from NAFTA mostly have small but negative and statistically significant impacts on crop acreage for all three field crops after the implementation of NAFTA (1994-2022).

Figure 2.5 provides the estimated effects of trade shock on the change in crop acreage from pre-NAFTA to the post-NAFTA years. The results with trade shocks measured by the U.S. market share shows that the decrease in U.S. export competitiveness leads an increase in the changes in crop acreage from pre-NAFT to post-NAFTA years for all crops, although the magnitude of estimated coefficients is different by crops.

**Effects of trade shocks on crop yield**

In figure 2.5, figures in the first row present the estimated effects of trade shocks measured by RCA on the change in crop yield from pre-NAFTA period. In the results with trade shocks based on RCA, we find that trade shocks from NAFTA mostly had small but negative and statistically significant impacts on crop acreage for all three field crops after the implementation of NAFTA (1994-2022). The results show that the effects of trade shocks on the change in crop yield are generally small and positive after 1999 for corn, but the effects for soybeans and wheat are mostly small and negative in post-NAFTA period.

In figure 2.5, figure in the second row provide the estimated effects of trade shock measured by market share on the change in crop yield from pre-NAFTA to the post-NAFTA period. For corn, the results shows positive impacts of trade shock on the change in corn yield for most years. However, for soybeans and wheat, we find that the decrease in U.S. market share leads an increase in crop yield from pre-NAFT to most of post-NAFTA years.

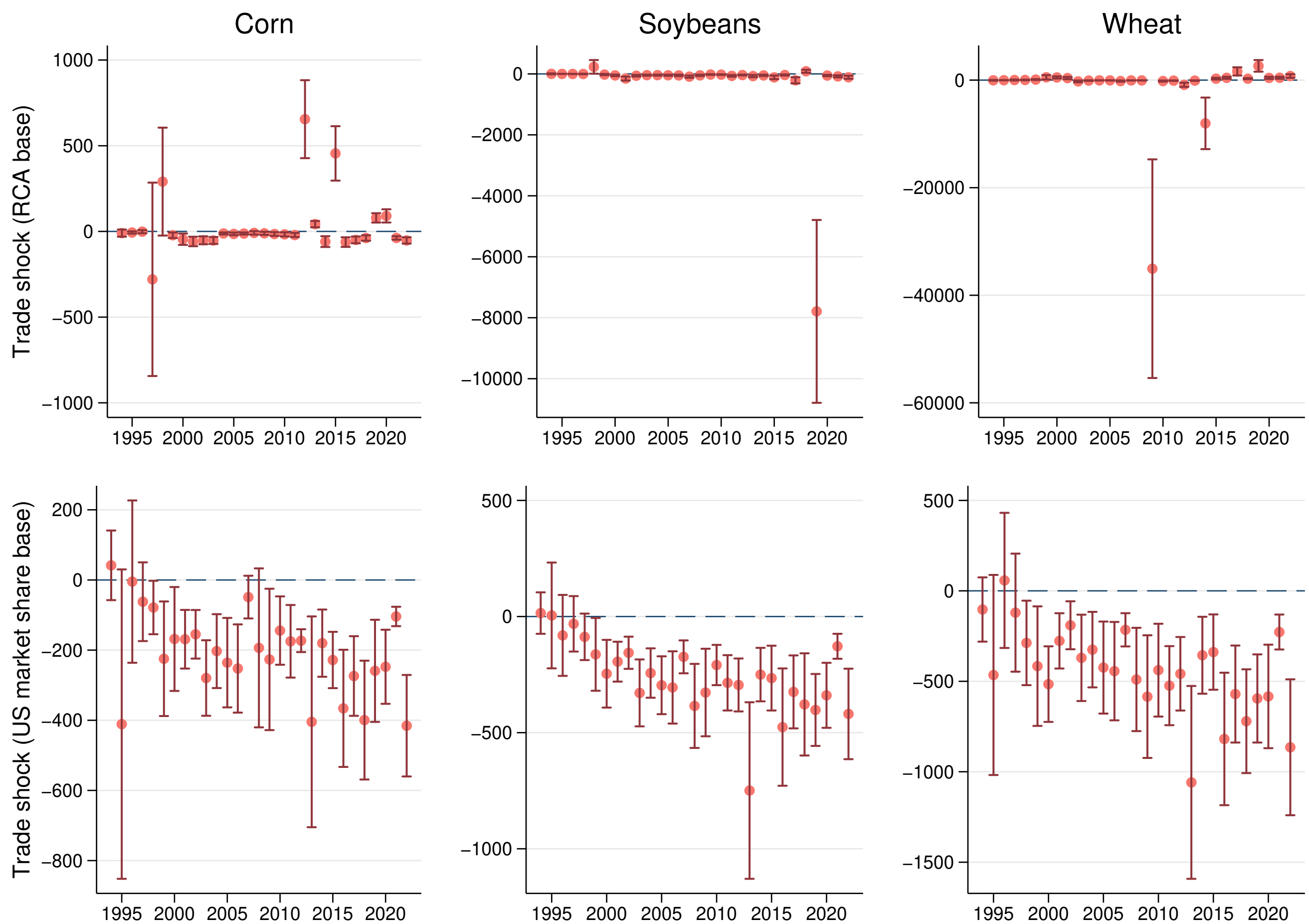


Figure 2.4: Effects of trade shock on crop acreage by year

Note: The estimated coefficients for each year are presented along with their corresponding 95% confidence intervals. The standard errors are clustered by state.

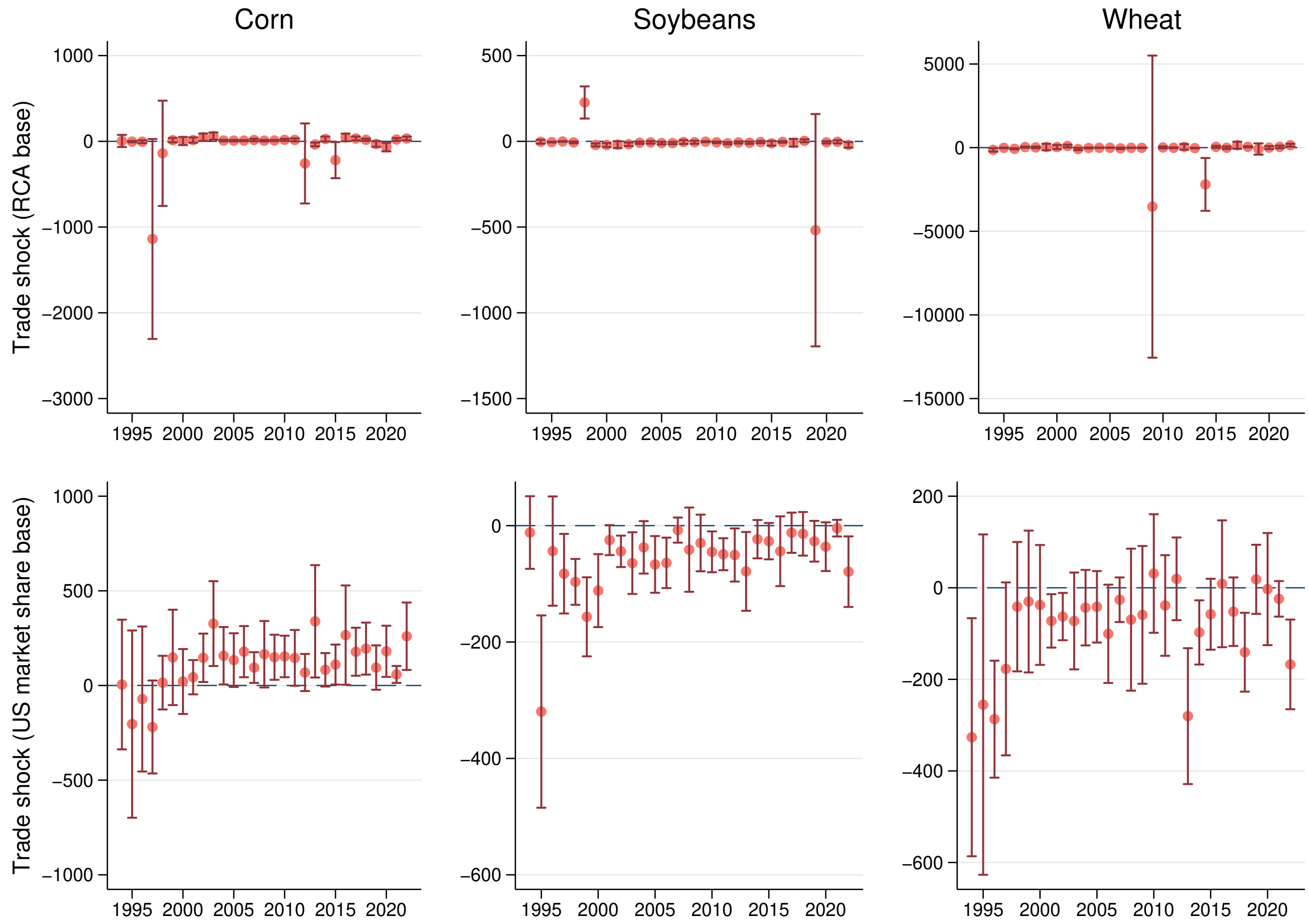


Figure 2.5: Effects of trade shock on crop yield by year

Note: The estimated coefficients for each year are presented along with their corresponding 95% confidence intervals. The standard errors are clustered by state.

### 2.4.3 Long difference model results

Tables 2.4-2.9 show the results of panel LD model estimation for each crop. We estimate the equation 2.7 separately for each 3-year interval from 1994 to 2022 to examine the dynamic effects of trade shock on changes in crop acreage and yield across different stages of NAFTA. In tables 2.4-2.9, columns (1)-(4) report the estimates for the short-run effect of trade shock from pre-NAFTA to years where tariff phasing out. Columns (5)-(6) report the medium-run effect of trade shock from pre-NAFTA to years of tariff elimination. Columns (7)-(8) report the results from the long-run effect of trade shock from pre-NAFTA to the recent 3 years. Every odd column reports results with localized trade shock measured by RCA, and every even column reports results with localized trade shock measured by the U.S. market share.

**Short-run, medium-run, long-run effects of trade shocks on crop acreage**

Table 2.4 shows the results of panel LD estimation on corn acreage. All estimates of trade shocks are negative and statistically significant except for those of short-run effect, indicating that counties facing less export competitiveness derived from declines in RCA experience an increase in corn acreage over the study period. The point estimates in columns (3)-(4) indicate that counties facing a decrease in RCA experience the expansion of corn acreage ranging from 41 thousand to 124 thousand acres from 1991 to 1999. The magnitude of effects of trade shock from NAFTA gets larger over time, showing that counties facing a level of decrease in the U.S. RCA for corn experienced a statistically significant increase in corn acreage expansion from 1991 to 2023, ranging from 100 thousand to 244 thousand acres (columns (7)-(8)).

Table 2.5 shows the results of panel LD estimation on soybean acreage. Across all stages of NAFTA, we find that trade shocks have negative impacts on expansion of soybean acreage and the magnitude of impacts increased over time. From 1991 to 1996, the estimated coefficients are ranging from -34.06 to -1.062, which indicates that a decrease in a level of trade shock causes soybean acreage expansion by about 1,062-34,060 acres. The point estimates in column (7)-(8) suggest that a decline in trade shocks positively and significantly increases soybean acreage growth by about 83 thousand to 247 thousand acres.

Table 2.6 shows the results of panel LD estimation on wheat acreage growth. Unlike the results for corn and soybeans, we observe different effects of trade shocks on wheat acreage depending on how we measure the trade shocks. When we measured trade shocks by changes in RCA, the estimated effects of trade shocks on soybean acreage grows significantly over time, indicating that a level of improved RCA causes increases in soybean acreage growth by about 101 thousand acres in 1991-1999 and about 531 thousand acres in 1991-2022. When trade shock is based on U.S. market share, the estimated coefficients are all negative over all periods of time, suggesting consistent negative effects of trade shocks.

**Short-run, medium-run, long-run effects of trade shocks on crop yield**

Table 2.7 shows the results of panel LD estimation on corn yield. All estimates of trade shocks are positive and statistically significant except for those of short-run effect, indicating that counties facing growth in RCA experience an increase in corn yield over the study period. The point estimates of trade shocks based on RCA indicate that counties facing an increase in RCA experience a significant increase in corn yield ranging from 28.3 to 56.8 bushels per acre in the medium- and long-term. When we measure trade shocks by U.S. market share in NAFTA countries, the results suggest that a level of increase in trade shocks increases corn yield by about 94.3-159.8 bushels per acre in the medium- and long-term of NAFTA.

On the other hand, the effects of trade shocks on soybean yield are opposite to those on corn, Table 2.8 shows the results of panel LD estimation on soybean yield. We find that trade shocks have negative impacts on soybean yield over time. From 1991 to 1999, the estimated coefficients are ranging from -11.64 to -69.82, indicating that a level of decrease in trade shock causes increase in soybean yield by about 11.6-69.8 bushels per acre. However, in the long-term, trade shocks are positively associated with soybean yield, but the results are not statistically significant.

Table 2.9 shows the results of panel LD estimation on wheat yield. We observe that the short-run effects of trade shocks are negative, indicating that a level of decrease in trade shock leads to a level of increase in the wheat yield growth by about 35.1-230.5 bushels per acre from 1991 to 1996. For the medium-run and long-run effects on wheat yield, the RCA base trade shock positively affects wheat yield, but the U.S. market share base trade shock negatively influences wheat yield even the results are not statistically significant.

Table 2.4: Short-run, medium-run, and long-run effects of trade shocks on corn acreage

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1994-1996 | | 1997-1999 | | 2000-2002 | | 2020-2022 | |
| $L.Trade$ (RCA) | -2.467 | | -41.78** | | -52.09*** | | -100.2*** | |
| | (4.675) | | (19.42) | | (13.36) | | (23.37) | |
| Competing crop 1 | 3.346 | | 15.49* | | 49.24*** | | 29.58*** | |
| | (2.363) | | (8.060) | | (12.99) | | (10.47) | |
| Competing crop 2 | 16.89 | | -57.61*** | | -254.2 | | -213.0*** | |
| | (11.51) | | (20.45) | | (207.9) | | (62.03) | |
| $L.Trade$ (U.S. market share) | | -51.00 | | -124.3** | | -169.2*** | | -244.1*** |
| | | (94.48) | | (54.54) | | (44.31) | | (57.01) |
| Competing crop 1 | | 116.3 | | 92.11* | | 126.9*** | | 87.98*** |
| | | (82.28) | | (48.03) | | (33.99) | | (31.18) |
| Competing crop 2 | | 111.6 | | 170.7*** | | 41.14 | | 174.0*** |
| | | (75.74) | | (60.59) | | (33.30) | | (50.54) |
| Observations | 2,164 | 2,164 | 2,067 | 2,067 | 2,052 | 2,052 | 1,508 | 1,508 |

Note: Weather variables and state fixed effect are included. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Short-run, medium-run, and long-run effects of trade shocks on soybean acreage

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1994-1996 | | 1997-1999 | | 2000-2002 | | 2020-2022 | |
| *L.Trade* (RCA) | -1.062 | | -15.41 | | -79.00*** | | -83.11*** | |
| | (2.116) | | (10.69) | | (17.47) | | (16.55) | |
| Competing crop 1 | 4.944 | | 74.48** | | 69.94*** | | 19.76 | |
| | (4.049) | | (29.71) | | (14.13) | | (15.17) | |
| Competing crop 2 | 7.772 | | -61.13* | | -1,778** | | -599.0*** | |
| | (10.17) | | (31.16) | | (712.6) | | (138.0) | |
| *L.Trade* (U.S. market share) | | -34.06 | | -84.98 | | -205.3*** | | -247.7*** |
| | | (73.11) | | (62.25) | | (45.47) | | (49.33) |
| Competing crop 1 | | 94.24 | | 202.9** | | 229.7*** | | 48.17 |
| | | (81.86) | | (83.72) | | (46.57) | | (37.00) |
| Competing crop 2 | | 48.91 | | 173.5* | | 282.9** | | 488.5*** |
| | | (66.72) | | (90.04) | | (113.1) | | (112.5) |
| Observations | 1,608 | 1,608 | 1,608 | 1,608 | 1,602 | 1,602 | 1,368 | 1,368 |

Note: Weather variables and state fixed effect are included. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.6: Short-run, medium-run, and long-run effects of trade shocks on wheat acreage

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1994-1996 | | 1997-1999 | | 2000-2002 | | 2020-2022 | |
| *L.Trade* (RCA) | -16.71 | | 101.3* | | 1,834*** | | 530.9*** | |
| | (21.31) | | (57.25) | | (517.5) | | (108.4) | |
| Competing crop 1 | -2.882 | | -10.99 | | -16.06 | | -5.833 | |
| | (2.372) | | (22.17) | | (13.24) | | (18.32) | |
| Competing crop 2 | 1.364 | | 7.204 | | 14.73 | | 9.428 | |
| | (1.364) | | (7.062) | | (9.554) | | (11.87) | |
| *L.Trade* (U.S. market share) | | -108.9 | | -297.4* | | -291.7*** | | -432.9*** |
| | | (140.7) | | (168.0) | | (82.33) | | (88.39) |
| Competing crop 1 | | -49.61 | | -27.44 | | -51.37 | | -13.95 |
| | | (46.14) | | (64.59) | | (43.09) | | (44.68) |
| Competing crop 2 | | 43.89 | | 41.79 | | 37.88 | | 28.02 |
| | | (48.54) | | (42.74) | | (24.72) | | (35.41) |
| Observations | 1,997 | 1,997 | 1,807 | 1,807 | 1,730 | 1,730 | 958 | 958 |

Note: Weather variables and state fixed effect are included. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.7: Short-run, medium-run, and long-run effects of trade shocks on corn yield

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1994-1996 | | 1997-1999 | | 2000-2002 | | 2020-2022 | |
| *L.Trade* (RCA) | 4.428 | | 56.82** | | 28.26** | | 53.77*** | |
| | (7.220) | | (25.07) | | (13.79) | | (11.35) | |
| Competing crop 1 | 3.526 | | 9.978 | | 18.93 | | 6.928 | |
| | (3.660) | | (10.21) | | (15.84) | | (7.366) | |
| Competing crop 2 | -34.14 | | -34.39 | | -469.8 | | 68.85 | |
| | (21.46) | | (26.90) | | (383.8) | | (68.53) | |
| *L.Trade* (U.S. market share) | | 104.2 | | 159.8** | | 94.26** | | 129.8*** |
| | | (146.5) | | (63.94) | | (44.98) | | (27.84) |
| Competing crop 1 | | 118.9 | | 67.76 | | 48.54 | | 21.17 |
| | | (128.2) | | (58.46) | | (41.12) | | (22.00) |
| Competing crop 2 | | -223.3 | | 97.68 | | 74.92 | | -56.63 |
| | | (142.6) | | (79.76) | | (61.10) | | (55.85) |
| Observations | 2,085 | 2,085 | 1,996 | 1,996 | 1,987 | 1,987 | 1,491 | 1,491 |

Note: Weather variables and state fixed effect are included. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Short-run, medium-run, and long-run effects of trade shocks on soybean yield

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1994-1996 | | 1997-1999 | | 2000-2002 | | 2020-2022 | |
| *L.Trade* (RCA) | -1.768 | | -11.64*** | | -10.56*** | | 0.134 | |
| | (1.085) | | (3.347) | | (3.677) | | (3.595) | |
| Competing crop 1 | 3.372 | | 19.45** | | 7.219* | | 14.01*** | |
| | (2.254) | | (8.165) | | (3.987) | | (4.908) | |
| Competing crop 2 | -14.37 | | -11.16 | | 3.684 | | 27.95 | |
| | (9.162) | | (10.78) | | (100.3) | | (29.96) | |
| *L.Trade* (U.S. market share) | | -62.00 | | -69.82*** | | -27.21*** | | 0.406 |
| | | (37.83) | | (20.19) | | (9.581) | | (10.72) |
| Competing crop 1 | | 72.17 | | 56.53** | | 23.06* | | 34.17*** |
| | | (45.01) | | (22.85) | | (13.02) | | (11.97) |
| Competing crop 2 | | -94.13 | | 31.78 | | -0.785 | | -22.80 |
| | | (60.29) | | (32.12) | | (16.03) | | (24.43) |
| Observations | 1,588 | 1,588 | 1,546 | 1,546 | 1,510 | 1,510 | 1,274 | 1,274 |

Note: Weather variables and state fixed effect are included. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2.9: Short-run, medium-run, and long-run effects of trade shocks on wheat yield

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1994-1996 | | 1997-1999 | | 2000-2002 | | 2020-2022 | |
| *L.Trade* (RCA) | -35.07** | | 16.63 | | 263.7 | | 38.71 | |
| | (13.87) | | (23.79) | | (179.2) | | (28.84) | |
| Competing crop 1 | 4.446 | | 13.79 | | 7.800 | | 5.691 | |
| | (4.846) | | (18.33) | | (9.062) | | (7.236) | |
| Competing crop 2 | 1.425 | | -1.769 | | 9.166 | | 10.12* | |
| | (2.087) | | (5.940) | | (7.253) | | (5.751) | |
| *L.Trade* (U.S. market share) | | -230.5** | | -48.91 | | -42.21 | | -31.55 |
| | | (91.91) | | (69.95) | | (28.61) | | (23.52) |
| Competing crop 1 | | 100.9 | | 43.54 | | 23.91 | | 13.95 |
| | | (96.96) | | (51.54) | | (29.92) | | (17.66) |
| Competing crop 2 | | 47.06 | | -10.85 | | 24.25 | | 30.14* |
| | | (73.15) | | (35.61) | | (18.55) | | (17.13) |
| Observations | 1,958 | 1,958 | 1,789 | 1,789 | 1,717 | 1,717 | 948 | 948 |

Note: Weather variables and state fixed effect are included. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

## 2.5 Conclusion

Better accessibility to foreign markets provides opportunities for U.S. agricultural producers to gain from trade. Gains may come from changes in the relative price of crops due to increases in foreign market demand. This may affect crop supply by changing producers' expectations of the profitability for crops that experienced greater relief from trade barriers, resulting in increasing acreage of crops that have faced more tariff reductions or better market accessibility.

Focusing on the major field crops, corn, soybeans, and wheat, we examine the effects of localized trade exposure on U.S. crop acreage and yield. Using a comprehensive dataset on crop production and bilateral trade data from 1991 to 2022, and localized trade exposure, we find that trade shocks from NAFTA have heterogeneous impact on crop acreage and yield by crop and different time period. The results show some negative impacts of trade shocks on corn acreage and soybean acreage on average annually and the negative impacts in the long-term. On the other hand, we find that trade shocks after implementation of NAFTA cause increasing corn yield over all time periods, while those lead an average annual increase in soybean yield, but decreases in the long-term.

While positive responses are more intuitive, we find negative effects for some crops and for some time periods. These may come from the fact that counties and crops with lower export competitiveness may respond more sensitively to trade shocks that made the crops more profitable. Although we find significant and differential effects of trade shocks, uncovering mechanisms remains for future studies. Such mechanisms may range from input use, and technology adoption, to policy interventions.

# Chapter 3

# Impacts of North American Free Trade Agreement on farm profitability and survival

## 3.1 Introduction

U.S. agriculture has been experiencing increases in exports to foreign markets over the last three decades with global trade liberalization. Specifically, the North American Free Trade Agreement (NAFTA) boosted agricultural trade among the United States, Canada, and Mexico through the relaxing trade barriers among the three countries. With better accessibility to global markets, U.S. agricultural producers may gain or lose from trade. The potential benefits are particularly pronounced for exporters, who experience significant reductions in tariffs on agricultural commodities that they produce as a result of trade liberalization. On the other hand, if individual farm operators lose their competitiveness in producing and exporting products, it would impact farm business decisions on input use, crop choice, or exit from the market at worst. Hence, it becomes important to understand the impact of trade exposure on the profitability of farms and farm survival, with a keen focus on identifying the individualized effects that stand to gain (or lose) from improved access to foreign markets.

The objective of this study is to examine how the greater trade exposure from NAFTA affects the profitability of farms and, as a result, how changes in the profitability after the implementation of NAFTA have impacts on the survival of farms. To do so, we estimate the effects of trade exposure on farm profit using farm-level panel data and employ a duration model to investigate the effects of trade exposure on farm exit.

In this study, we focus on NAFTA and Kansas farms for a couple of reasons. First, Canada and Mexico are major agricultural trade partners of the United States. Second, since NAFTA came into effect, the agreement has gradually relieved almost all barriers to trade and investment among the three countries, resulting in increases in the size of U.S. agricultural trade with members in NAFTA. In addition, due to the limited accessibility to farm-level data for the entire country, we focus on the farms that produced major field crops (corn, wheat, soybeans) in Kansas from 1991 to 2022.

The literature on the local impacts of trade policy finds negative correlations between imports (exports) and local labor markets (e.g., Autor et al., 2013; Dix-Carneiro and Kovak, 2017; He, 2020), but less attention has been paid to the impact of better access to foreign markets on the profitability of agriculture across the U.S. counties. One exception is Yu et al. (2022), who showed that more export exposure improved the returns to U.S. agriculture. Their findings indicate that the heterogeneous export effects on farm returns may come from the changes in profitability of crops that are exposed to greater accessibility, yet the direct estimation of trade exposure on individual farms' profitability has not been documented.

Some studies analyze the effect of NAFTA on agriculture. Burfisher et al. (2001) find that the agricultural sector in the United States benefited from NAFTA by increased demand for U.S. agricultural products, and Prina (2013) finds that Mexican small farmers tended to benefit from the agreement on balance. However, the empirical evidence on the effects of NAFTA on individual farm outcomes is limited.

While several studies have paid attention to the survival of firms in response to changes in trade barriers, their theoretical and empirical findings imply the need for more empirical assessment. A seminal paper by Melitz (2003) argues and proves theoretically that relatively high-productive firms extend their market shares and use resources at the expense of low-productive firms, which forces low-productive firms to exit. Hence, relatively productive firms may benefit from increased access to foreign markets as exporters, while low-productive firms may suffer from low profits due to the increased market competition as non-exporters, resulting in a lower probability of survival. Findings from Baggs (2005), who studies the United States-Canada free trade agreement, indicate that export partner's tariff reductions increase the likelihood of survival for firms in the exporting country.

Within the agricultural sector, literature on farm survival has found that agricultural support payments exhibit a negative impact on the farm exit rate (e.g., Key and Roberts, 2006; Kazukauskas et al., 2013; Storm et al., 2015). On the other hand, findings from other studies indicate that receiving more government payments leads to a faster rate of farm exits (e.g., Goetz and Debertin, 2001). In addition, several studies have explored other determinants of farm survival. These determinants include farm characteristics (e.g., Kimhi and Bollman, 1999), decoupled subsidies (e.g., Key and Roberts, 2006; Kazukauskas et al., 2013), neighboring interdependence (e.g., Storm et al., 2015), crop insurance (e.g., Kim et al., 2020; Santeramo et al., 2016), and cooperative extension (e.g., Goetz and Davlasheridze, 2017). However, there is a lack of empirical estimates on the impact of trade policy on farm survival.

Our contribution to the literature is twofold. We quantify the effect of greater exposure to export markets for individual farms and their economic outcomes. While there have been theoretical discussions and some empirical findings at a more aggregate level, the evidence is limited for individual farms. We also provide a novel discussion on measuring trade exposure for individual farms exploiting the recent international trade literature (e.g., Autor et al., 2013; Hakobyan and McLaren, 2016).

## 3.2 Data and variable descriptions

We construct a farm-level dataset including information on farm production, farm characteristics, and farm-level trade exposure. We combine data from the World Integrated Trade Solution (WITS) database, the Food and Agriculture Organization (FAO) of the United

Nations database, and the Kansas Farm Management Association (KFMA). We use data on corn, soybeans, and wheat for the period of 1991-2022.

### 3.2.1 Trade and farm production data

Trade data is obtained from UN Commodity Trade (UN Comtrade) using the WITS database. We extract the exporter-importer pair from 1991 to 2022 for all countries and all goods using 6-digit Harmonized Tariff Schedule (HS) codes. Next, we group trade values into commodity categories based on the concordance code provided by the USDA Foreign Agricultural Service (FAS) Global Agricultural Trade System (GATS).[1]

To compute the farm-level trade exposure from NAFTA, we consider two different measures of the U.S. export competitiveness; one is the revealed comparative advantage (RCA), and the other is the U.S. market share in partner countries. The RCA, suggested by Balassa (1965), is a measure of a country's comparative advantage in producing and exporting a good relative to total world exports of that good. We define the U.S. RCA in exporting crop $j$ as the U.S. share of world exports in crop $j$ over the U.S. share of total world exports in all goods. The RCA is calculated using bilateral export data as follows:

$$RCA_{jt}^{U.S.} = \frac{\frac{export_{jt}^{U.S.}}{export_{jt}^{WLD}}}{\sum_{k}^{N}\left(\frac{export_{kt}^{U.S.}}{export_{kt}^{WLD}}\right)} \tag{3.1}$$

where $export_{jt}^{U.S.}$ is U.S. exports of crop $j$ to the world including Canada and Mexico, and $export_{jt}^{WLD}$ is total exports of crop $j$ from all countries to the world. The numerator of RCA is the U.S. share of world trade in crop $j$, and the denominator is the U.S. share of total exports in all goods $k \in \{1, 2, \ldots, N\}$. If RCA is greater than 1, it indicates that the U.S. has a revealed comparative advantage in the production and export of that good. The higher the value of RCA in crop $j$ indicates a stronger export advantage in that crop.

Another measure of U.S. export competitiveness is the U.S. market share in NAFTA

[1] To group 6-digit HS codes into categories for major field crops, we use 100590 for corn; 120100, 120190 for soybeans; 100110, 100119, 100190, 100199 for wheat.

countries, which is defined as a ratio of the U.S. export volume over the consumption volume of crop $j$ in NAFTA partners.

$$U.S.\ market\ share = \frac{export_{jt}^{U.S.-NAFTA}}{consumption_{jt}^{NAFTA}} \tag{3.2}$$

where $export_{jt}^{U.S.-NAFTA}$ is the export volume of the U.S. for crop $j$ to Canada and Mexico and $consumption_{jt}^{NAFTA}$ is the consumption volume of crop $j$ in Canada and Mexico, which is calculated for crop $j$ as NAFTA countries' production minus total exports plus total imports. Data on U.S. export quantity is from USDA FAS (USDA FAS, 2024) and data on crop consumption is from FAO Food and Agriculture database (WTO, 2024).

Figure 3.1 shows U.S. export value to NAFTA partners and U.S. market share in NAFTA countries by crop from 1991 to 2022. Each color represents U.S. export value and market share for different crops: red for corn, blue for soybeans, and green for wheat. Overall, the left figure highlights an upward trend in U.S. export values over the study period. From 1991 to 2022, U.S. exports to Mexico and Canada increased significantly, rising from $122.3 million to $10.0 billion for corn, $255.6 million to $6.1 billion for soybeans, and $28.3 million to $2.6 billion for wheat. The right figure shows the U.S. market share in NAFTA countries, highlighting upward trends with variations. In particular, the U.S. market share for soybeans increased significantly from 50.4% to 99.2% after the implementation of NAFTA, while it shows a downward trend between 2009 and 2017. For corn and wheat, the U.S. market shares more than doubled between 1991 and 2022.

To estimate the impacts of NAFTA on individual farms, we utilize the Kansas Farm Management Association (KFMA)[2] data from 1991 to 2022. KFMA data provides detailed information on farm characteristics and production, such as farm types, number of operators, number of workers, operator's age, crop and livestock production, various farm income and expenses, etc. Although other administrative data, such as the Census of Agriculture, provides comprehensive farm financial and crop production for farm population, the Census

[2]KFMA is one of the largest farm management programs in the U.S., which consists of six regional associations that maintain historical Kansas farm-level information.

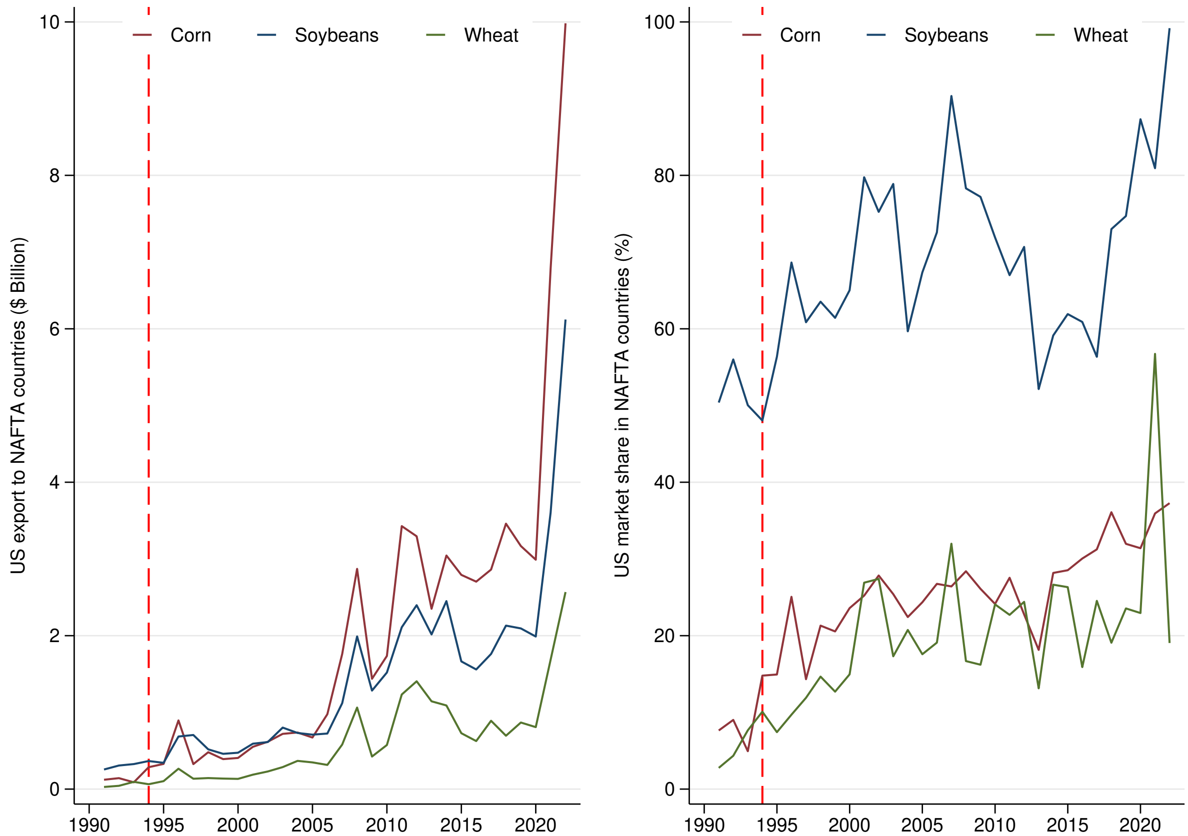


Figure 3.1: U.S. export value to NAFTA countries and market share in NAFTA countries
Note: The value of export is adjusted by 2020 U.S. dollars using the producer price index from the U.S. Bureau of Labor Statistics. The red dashed line indicates the year of NAFTA implementation, 1994.

data is taken only once every five years, so it is unclear how to figure out the survival of farms in consecutive years. Thus, the data from KFMA is valuable for the analysis of farm exits in the sense that the periods of KFMA data are more than 40 years, and the KFMA collects detailed financial and production information. For analysis, we restrict our samples to (i) the farms consecutively observed in our dataset in the pre-NAFTA period (1991-1993), (ii) farms that produced major field crops (corn, wheat, soybeans), (iii) farms that dedicated labor to crop production (crop-labor share $> 0.8$).

Table 3.1 provides the descriptive statistics of the selected variables, including net farm income at the level, shares of crop acres, and farm-level trade exposure based on two different measures of U.S. export competitiveness for the main sample from unbalanced panel data. The overall average net farm income for a Kansas farm is about $62.7 thousand. By subsamples of time periods, average net farm income has been increased significantly from $27.2 thousand in 1991-1993 to $268.9 thousand in 2020-2022. In crop acres shares, the average share of corn increased from 10.3% in 1991-1993 to 23.5% in 2020-2022. For soybeans, the average share of soybeans increased from 17.2% in 1991-1993 to 42.2% in 2020-2022, indicating a greater reliance on corn production. On the other hand, wheat experienced slight declines in its share, from 37.9% in 1991-1993 to 22.2% in 2020-2022.

Table 3.1: Descriptive statistics of farm-level observations by year

| | (1) Overall | (2) 1991-1993 | (3) 2020-2022 |
|---|---|---|---|
| Net farm income ($thousand) | 62.72 | 27.20 | 268.92 |
| | (135.95) | (34.17) | (366.75) |
| Share of Corn (%) | 15.41 | 10.30 | 23.51 |
| | (18.06) | (15.16) | (18.49) |
| Share of Soybeans (%) | 24.32 | 17.24 | 42.19 |
| | (24.34) | (21.45) | (23.56) |
| Share of Wheat (%) | 33.73 | 37.92 | 22.18 |
| | (23.69) | (21.58) | (21.19) |
| Trade exposure (RCA base) | 2.22 | 1.98 | 2.08 |
| | (1.16) | (0.95) | (1.15) |
| Trade exposure (U.S. market share base) | 0.19 | 0.12 | 0.32 |
| | (0.14) | (0.11) | (0.17) |
| Observations | 14,090 | 2,067 | 490 |

Note: Standard deviations are in parentheses. All variables measured in U.S. dollars are adjusted using the producer price index from the U.S. Bureau of Labor Statistics. Descriptive statistics for all variables are provided in Appendix B.

### 3.2.2 Farm-level trade exposure to NAFTA

Our explanatory variable of interest is farm-level exposure to trade shock from NAFTA, which is a measure of the degree to which individual farms are exposed to exports. The key challenge is to construct a farm-level variable that allocates national-level trade shock to that of individual farms. To do so, we first hypothesize that U.S. farms have benefited (or lost) from NAFTA due to changes in the United States' export competitiveness and consider two different measures of U.S. export competitiveness; one is the revealed comparative advantage (RCA), and the other is U.S. market share in Canada and Mexico. Next, we use a farm's share of crop acreage as a share that allocates national-level shocks to individual farms. Thus, although all farms face the same changes in NAFTA-induced foreign market accessibility, differences in the crop mix of individual farms generate individual variations in trade shocks.

Since the RCA and U.S. market share calculations rely on annual trade and production values for Canada and Mexico, some may raise concerns about endogeneity issues. These concerns arise from the use of annual trade and production variables, which are aggregated using contemporaneous crop shares as weights. Thus, we compute the farm-level trade exposure using contemporaneous trade values and initial farm production shares in the pre-NAFTA period (1991-1993).

Motivated by Autor et al. (2013), we define farm-level trade exposure for farm $i$ in year $t$ using two different trade measures. First, RCA base farm-level trade exposure is as follows:

$$RCA \times Crop\ share_{it} = \sum_j RCA_{jt}^{U.S.} \times Crop\ Share_{ij0} \tag{3.3}$$

where $Crop\ Share_{ij0}$ is an initial crop share, which is defined as 3-year average of crop $j$ acreage over total crop acreage for farm $i$ in 1991-1993. $RCA_{jt}^{U.S.}$ is the U.S. revealed comparative advantage in exports of crop $j$ in year $t$, calculated using the equation 3.1.

Second, U.S. market share base farm-level trade exposure is as follows:

$$U.S.\ market\ share \times Crop\ share_{it} = \sum_j U.S.\ market\ share_{jt} \times Crop\ share_{ij0} \tag{3.4}$$

where $U.S.\ market\ share_{jt}$ is the share of U.S. export volume to NAFTA countries over NAFTA countries' consumption volume of crop $j$, calculated using the equation 3.2. $Crop\ Share_{ij0}$ is the initial crop share for farm $i$, crop $j$, and year $t$.

Figure 3.2 shows boxplots of the farm-level trade exposure computed using equations 3.3 and 3.4, for the regression samples to illustrate the distributions of trade exposure across farms by each year. The blue box and red box represent farm-level trade exposure variables with contemporaneous trade measure and crop shares and those with contemporaneous trade measure and initial crop shares, respectively. For farm-level trade exposure measured by RCA, the median and variations are relatively greater for contemporaneous trade exposure to NAFTA than those with initial crop share. For farm-level trade exposure based on U.S. market share in the NAFTA countries, both trade exposure variables have increased over the study period, while trade exposure with contemporaneous trade measure and crop shares has shown more upward trend than trade exposure with contemporaneous market share and initial crop share.

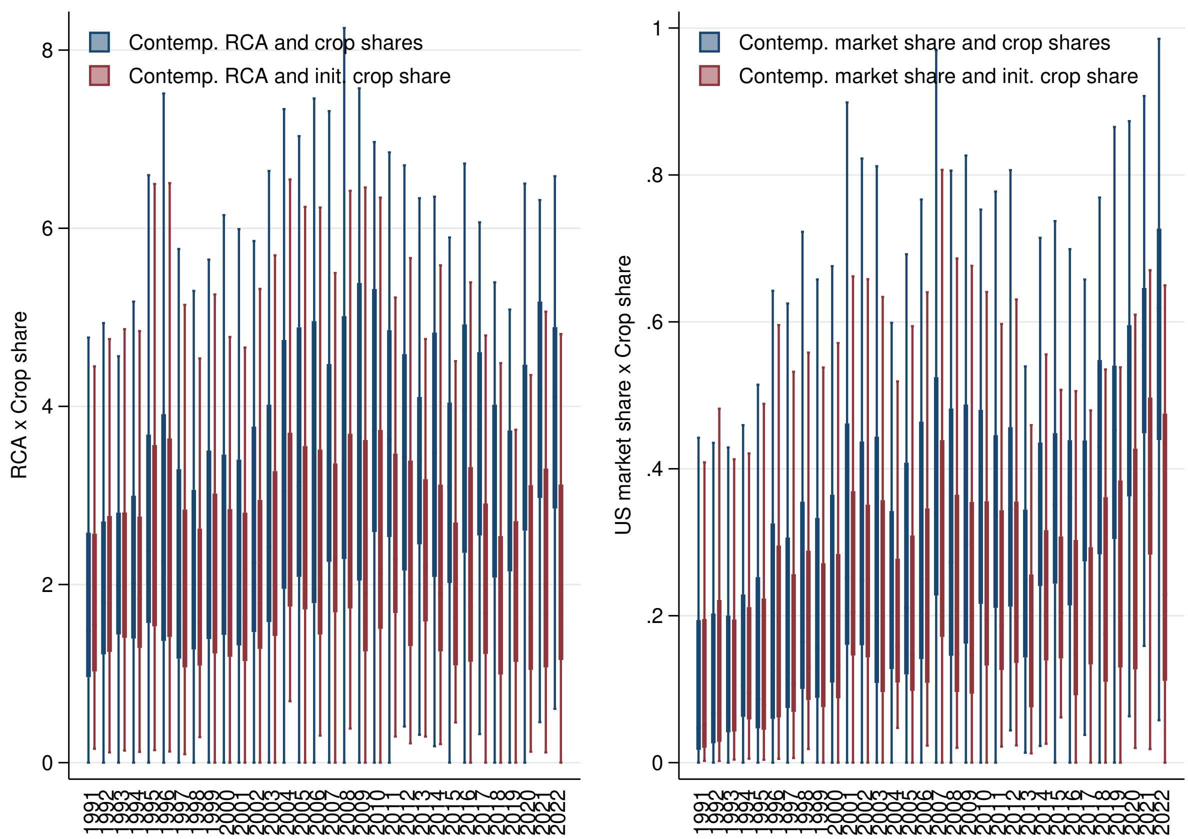


Figure 3.2: Boxplots of farm-level trade exposure

### 3.2.3 Definition of farm exit

The key component of farm survival analysis is how to define farm exit. In earlier studies, farms are considered to have exited, if they are no longer present in their dataset (e.g., Key and Roberts, 2006; Bontemps et al., 2013). However, in the case of KFMA data, some producers who participate in KFMA may not renew their annual membership while continuing to operate their farms.

Since farms voluntarily participate in KFMA, some may not renew their annual membership, and thus, it is possible for producers to be temporarily absent from the data even though they continue to operate their farms (Kim et al., 2020). To deal with the temporal absence of farms, Kim et al. (2020) defined farm exit based on the average longest length of consecutive missing years of farms. To be specific, farms are considered to have exited if they are absent for more consecutive years than the average maximum years of absence observed within the dataset. Following Kim et al. (2020), we also examine how long producers were missing from the complete KFMA data without any sample restrictions.

Table 3.2 presents the average consecutive missing years for farms that left KFMA and returned to KFMA for different starting years from 1991 to 1999 in the unrestricted sample. We consider the year in which a farm is first observed in the study period as its initial year of farming. We then count the number of consecutive years during which the farm is not observed until it reappears in the data. The average length of consecutive missing years ranged from 2.12 to 3.24, suggesting that it is possible for farms not to participate in the KFMA program for up to three years. We assume that a farm remains enrolled in the program despite its absence from KFMA data after 2020, given the likelihood of temporary non-participation. Therefore, this study defines a farm as having exited the program, if it does not participate in the KFMA for more than 3 consecutive years prior to the final year of the study period, which is 2022.

Table 3.2: Average length of observed consecutive missing years by year

| Initial year | Missing years | Number of observations |
|---|---|---|
| 1991 | 2.47 | 13,458 |
| 1992 | 3.24 | 2,048 |
| 1993 | 2.58 | 1,129 |
| 1994 | 2.46 | 819 |
| 1995 | 2.33 | 747 |
| 1996 | 2.33 | 761 |
| 1997 | 2.12 | 645 |
| 1998 | 2.55 | 534 |
| 1999 | 3.05 | 373 |

Note: If a farm disappeared from the dataset more than once, the longest consecutive missing years are counted.

## 3.3 Empirical specification

To assess the impact of NAFTA on farm-level outcomes, we face two key challenges: (i) individualizing the national- and crop-level trade shocks and (ii) identification of the effects of the changes in trade shocks. Our approach is largely motivated by the recent development in shift-share design literature (e.g., Autor et al., 2013; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). This section describes the empirical approach based on shift-share design and the duration model for assessing farm survival.

### 3.3.1 Dynamic effects on farm profit: Shift-share design

To estimate the dynamic effects of farm-level trade exposure due to NAFTA on farm profitability, this study utilizes "shift-share" specifications, motivated by literature (e.g., Bartik, 1991; Autor et al., 2013). Shift-share instruments for trade exposure are the weighted averages of trade exposure with weights reflecting heterogeneous shock exposure for individual farms. The farm-level exposure is constructed from shocks to crop sectors with individual farms' crop production shares measuring the shock exposure. Using the farm-level exposure, we specify the baseline model as follows:

$$Profit_{it} = \alpha_0 + \alpha_1 Trade_{it} + \Gamma X_{it} + u_i + e_t + \epsilon_{it} \tag{3.5}$$

Here, the dependent variable is net farm income for farm $i$ and year $t$, $Profit_{it}$, and the explanatory variable is farm-level trade exposure constructed from equations 3.3 and 3.4, $Trade_{it} \in \{RCA \times crop\ share_{it}, U.S.\ market\ share \times crop\ share_{it}\}$. $X_{it}$ denotes a set of controls, including the total value of farm capital, the total value of farm production, the total value of machinery and equipment, farm types, the number of operators, the number of workers, the number of family dependents, and the share of labor dedicated to crop production over labor dedicated to farming and ranching. $u_i$ and $e_t$ are farm and year fixed effects used to control for farm-specific and time-specific characteristics, and $\epsilon_{it}$ is an error term.

Since the trade restrictions, including tariffs, were gradually relieved until 2008, the effects of NAFTA on farms can be differential across different time periods after its enforcement. To identify these gradual impacts of NAFTA, we define the pre-NAFTA periods of 1991-1993 as the "base period" and compute annual trade shocks by taking the difference of variables from the base period to the specific year. Let $i$ and $t$ denote farm and time, respectively. The estimation model to examine the dynamic effects of trade exposure is as follows:

$$\Delta Profit_{it} = \beta_0 + \beta_1 \Delta Trade_{it} + B\Delta X_{it} + u_c + \epsilon_{it} \tag{3.6}$$

where $\Delta$ indicates the change in an average of a variable for farm $i$ in year $t$ from the initial value of the variable defined as an average from 1991 to 1993 (pre-NAFTA).[3] The trade shocks from NAFTA, $\Delta Trade_{it} \in \{\Delta RCA \times crop\ share_{it}, \Delta U.S.\ market\ share \times crop\ share_{it}\}$, are measured by the weighted average of the changes in RCA (or U.S. market share in the partner countries) for crop $j$ from those in the pre-NAFTA to year $t \in \{1994, 1995, \ldots, 2022\}$:

$$\Delta RCA \times crop\ share_{it} = \sum_j (RCA_{jt} - RCA_{j0}) \times Crop\ Share_{ij0}$$

[3] For example, $\Delta Profit_{it}$ is the change in average profit for farm $i$ in $t$ from the average profit in 1991-1993 (pre-NAFTA), i.e. $\Delta Profit_{it} = Profit_{it} - Profit_{i0}$.

and

$$\Delta U.S.\ market\ share \times Crop\ share_{it} = \sum_j (U.S.\ market\ share_{jdt} - U.S.\ market\ share_{jd0}) \times Crop\ share_{ij0}$$

In equation 3.6, $\Delta X_{ijt}$ denotes a vector of changes in each control variable from the pre-NAFTA period to year $t$, and $u_c$ indicates county fixed effect.

### 3.3.2 Effects on farm survival: Duration model

To estimate the impact of trade exposure due to NAFTA on farm survival, this study considers a duration model, i.e., Cox proportional hazard model (Cox, 1972) and the base year is 1994. We select the year 1994 as the base year because NAFTA was enforced in 1994. Thus, for the survival analysis, we additionally restrict our samples to the farms that appeared in our dataset every year from 1991 to 1994.

Due to the limitation of data, we do not observe the exit of farms that did not exit at the end of periods in our data and this may lead to the censoring problems. To deal with censoring problems, we consider the Cox proportional hazard model that can mitigate the standard right censoring problem (Key and Roberts, 2006). For a farm that survived until time $t$, the conditional probability of exiting after time $t$, a hazard function $h(\cdot)$ is as follows

$$h(t;\ Trade_i,\ X_i) = h_0(t)\exp(\gamma Trade_i + \Gamma X_i) \tag{3.7}$$

where $h_0(t)$ is the baseline hazard function, $X_i$ is a vector of control variables, and $Trade_i$ is a trade exposure computed by taking a difference in two different trade exposure variables between pre-NAFTA and 1994, i.e., $Trade_i = Trade_{i1994} - Trade_{i0}$.

The coefficient that we are interested in is $\gamma$, representing the treatment effect. It is interpreted as how the implementation of NAFTA impacts the likelihood of farms' survival through greater exposure to exports. The vector of control variables, $X$, includes individual operator's characteristics (e.g., the age of the operator, number of operators, number of workers, and number of family dependents).

## 3.4 Results

### 3.4.1 Effects of trade exposure on farm profit

Table 3.3 shows the regression results for the baseline model regarding the average effects of trade exposure based on equation 3.5. The first two columns of table 3.3 report the estimation results with RCA base trade exposure, while the last two columns report the results with U.S. market share base trade exposure. Columns (1) and (3) report the estimation results with trade exposure using contemporaneous trade shocks and crop share, while columns (2) and (4) report the results with trade exposure using contemporaneous trade shocks and initial crop shares. Overall, the findings suggest that farm-level trade exposure has a positive impact on farm profit on average.

Table 3.3: Effects of trade exposure on farm profit

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | Dependent variable: Farm profit | | | |
| Contemp. RCA and crop shares | -0.313 | | | |
| | (1.676) | | | |
| Contemp. RCA and init. crop share | | 0.425 | | |
| | | (2.935) | | |
| Contemp. market share and crop shares | | | 27.241** | |
| | | | (12.686) | |
| Contemp. market share and init. crop share | | | | 85.034*** |
| | | | | (22.145) |
| Observations | 12,023 | 12,023 | 12,023 | 12,023 |

Note: Control variables, farm and year fixed effects are included. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 3.3 presents the estimated coefficients of equation 3.6 by year using the shift-share variables, which are based on the difference in RCA and the difference in U.S. market share from the pre-NAFTA years to years in post-NAFTA periods (1994-2022). In the results, we find that trade shocks from NAFTA mostly had small but negative and significant impacts on farm profit from the beginning to middle periods of the implementation of NAFTA (1994-2009) for both trade shocks measured by the changes in RCA and U.S. market share. The results show that the effects of trade shocks fluctuated after 2009, but most of the results are not statistically significant in the long term. This suggests that the estimation results for the long-run effects exhibit high variability and are possibly influenced by unobserved factors other than trade values.

### 3.4.2 Effects of trade shock on farm exit

To examine the relationship between trade exposure and farm survival, we compare Kaplan-Meier survival function estimates for farms in the upper, middle, and lower trade exposure quartiles. The probability of farm survival is estimated for the groups by the size of trade exposure that farms exposed. The left figure of figure 3.4 shows that farms in the low quartile (Q25) are less likely to survive than those in the top quartile (Q75). In other words, farms that experienced larger trade shocks, as measured by RCA, have a higher probability of survival compared to farms that faced smaller trade shocks. The right provides results for trade shocks measured by U.S. market share. Unlike the results of the RCA base trade shock, it shows that farms that faced lower trade shocks are more likely to survive than farms that faced higher trade shocks.

Table 3.4 provides the estimates of the Cox model. Columns (1)-(2) report the estimation results with trade shocks using RCA, while columns (3)-(4) report the results with trade shocks using U.S. market share in NAFTA countries. The negative coefficients of trade shocks imply the likelihood of farm survival is increased as farms are exposed to the greater trade shock. Overall, the findings suggest that farm-level trade shock positively influences the rate of farm survival, when we measure trade shock using RCA. However, the impact is reversed when trade shock is measured by the U.S. market share, indicating that farms exposed to greater trade shocks are more likely to exit.

Table 3.4: Cox proportional hazard model estimation results

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | Dependent variable: Hazard rate | | | |
| Trade shock (RCA base) | -1.487** | -0.864 | | |
| | (0.667) | (0.698) | | |
| Trade shock (U.S. market share base) | | | 7.561*** | 4.276 |
| | | | (2.802) | (2.983) |
| Controls | No | Yes | No | Yes |
| Observations | 10,001 | 10,001 | 10,001 | 10,001 |

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

## 3.5 Conclusion

After the implementation of the North American Free Trade Agreement (NAFTA), one of the major trade agreements of the U.S., trade restrictions on some agricultural commodities were phased out over periods. Better accessibility to foreign markets provides opportunities for U.S. agricultural producers to gain from trade, while producers who lose comparative advantage in production lose from trade resulting in exit from the market.

Focusing on the field crop farms in Kansas, we study the impact of trade exposure on farm profitability and survival. Using the comprehensive dataset of farm production, bilateral trade, and farm-level trade shock from 1991 to 2022, we find that the average annual effects of farm-level trade exposure are positive on farm profit over the study period, but these effects are reversed in the long-term due to factors other than trade values. In addition, we estimate the impact of trade exposure on farm survival and find that farms that experienced greater trade exposure have a higher probability of survival compared to farms that faced lower trade exposure when trade shock is measured by the U.S. revealed comparative advantage in exporting crops. However, when trade shock is measured by U.S. market share in NAFTA countries, the results indicate a negative relationship between trade exposure and farm survival rate. The findings of this study show that better access to global markets has a significant impact on farm profits and the long-run viability of farm businesses. This underscores a need for a deep study of policies that enhance foreign market access for farms, particularly considering the dynamics in global agricultural trade.

Since we restricted samples to the crop farms in Kansas, we cannot conclude that better accessibility to foreign markets has a positive impact on farm profit and survival in general. Further investigations would be needed to provide additional policy implications.

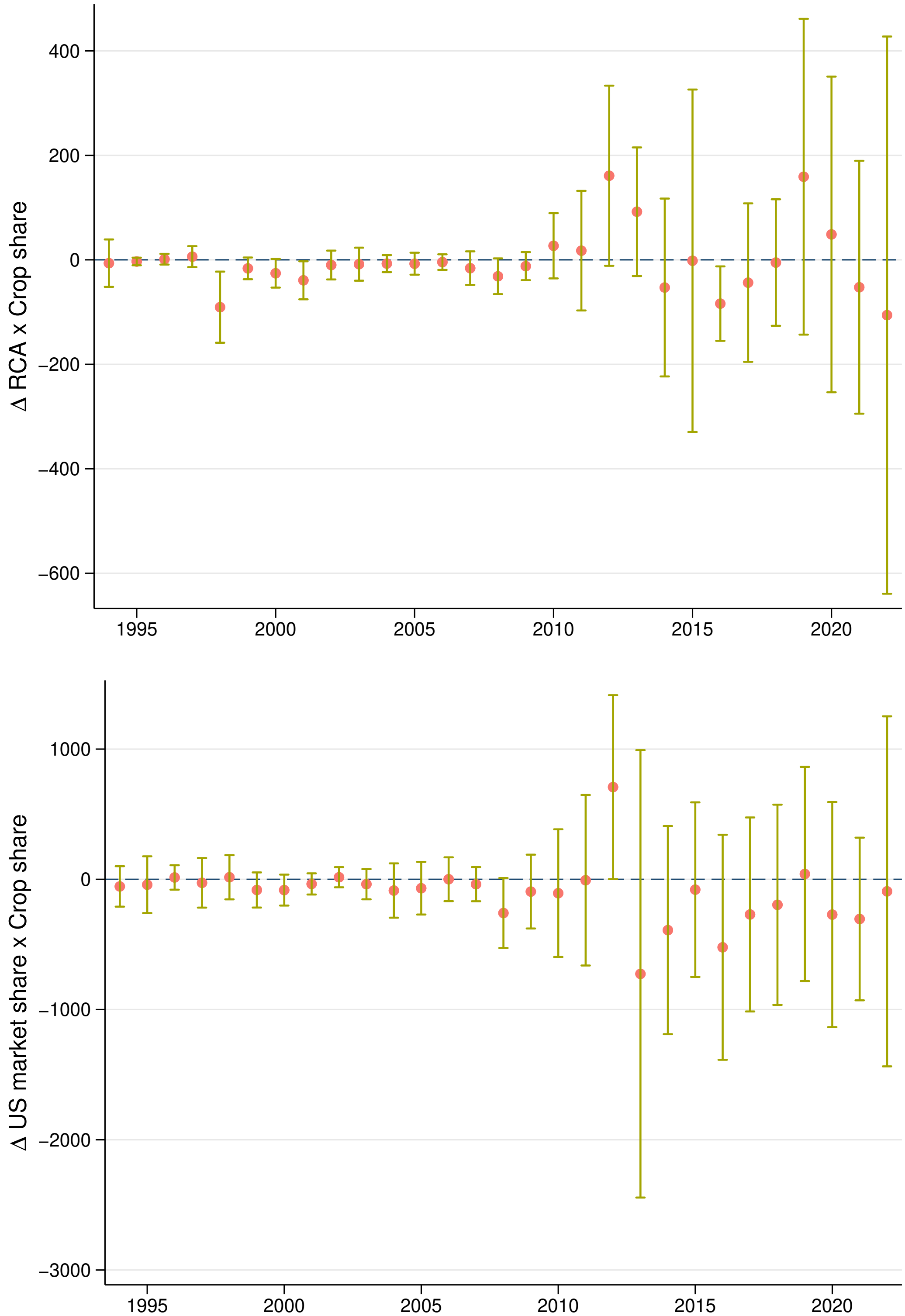


Figure 3.3: Effects of trade shock on farm profit by year

Note: The estimated coefficients for each year are presented along with their corresponding 95% confidence intervals. The standard errors are clustered by county.

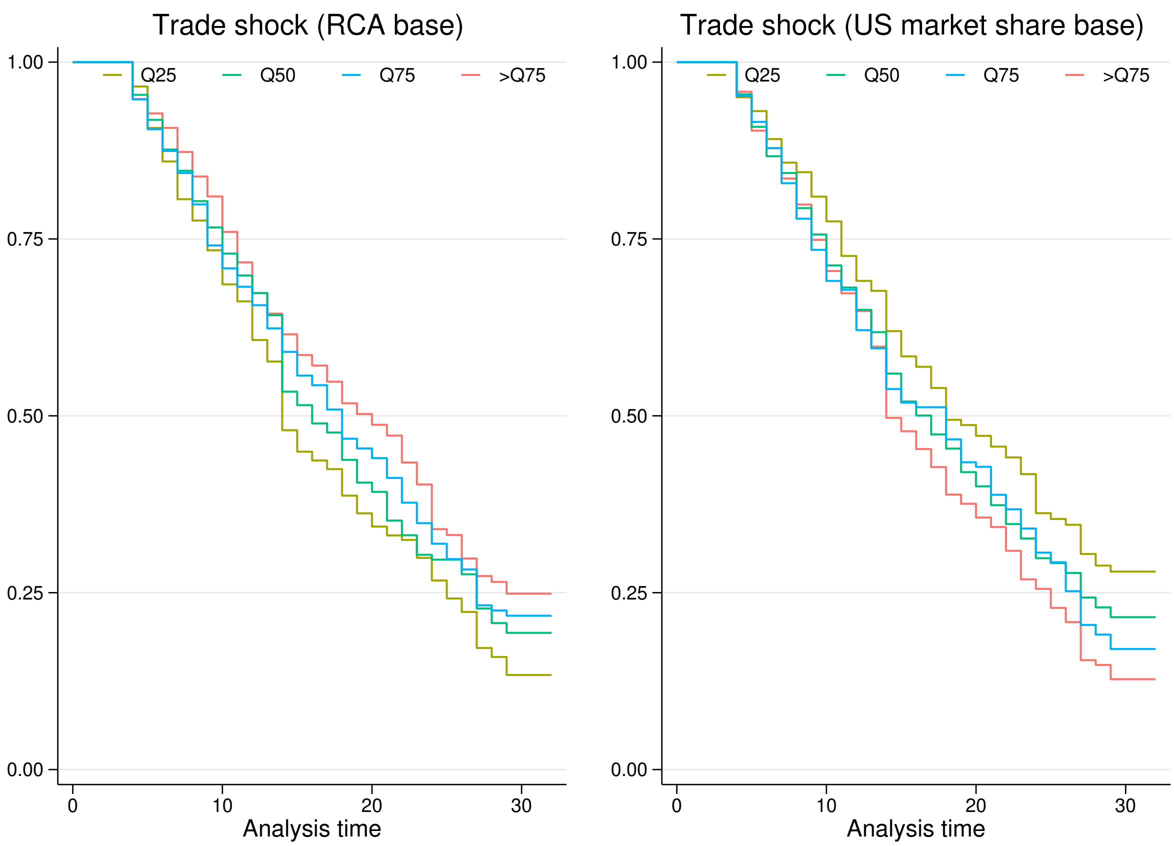


Figure 3.4: Kaplan–Meier survival curves by trade exposure quartiles

# Chapter 4

# Assessing differential impacts of a trade agreement using a quantile regression approach

## 4.1 Introduction

After the Doha Round of the World Trade Organization (WTO), regional or bilateral free trade agreements (FTAs) have increased around the world. According to the WTO, a total of 369 regional trade agreements were in force as of June 2024 (WTO, 2024). With the increasing number of trade agreements, the economic consequences of the trade agreements become more important (Benz and Yalcin, 2015; He, 2022; Hirsch and Oberhofer, 2020; Sun and Reed, 2010).

The objective of this study is to directly estimate the impacts of an FTA for an importing country, i.e., the Korea-Chile FTA, on the farm economy in South Korea. Using the farm-level panel data from 2003–2007 and a shift-share approach, we examine how this first free trade agreement for South Korea affected farm profitability. The case of the Korea-Chile FTA provides a unique opportunity to evaluate the impact of trade agreements on the agricultural sector of an importing country as the agreement has been the first major trade agreement that South Korea engaged with a major agriculture-exporting country.

South Korea has aggressively promoted trade agreements with various countries after the implementation of the Korea-Chile FTA.[1] Although some viewed the Korea-Chile FTA as having a low impact on South Korea's agriculture due to seasonal differences (Park and Koo, 2007), the potential substitutability across agricultural commodities from Korea and Chile might have negative impacts on the farm economy in Korea. Thus, we attempt to provide empirical evidence on the immediate effect of the trade agreement.[2]

Increasing imports of goods can reduce the profitability of the domestic producers of those goods or the prices of the factors that are employed to produce those goods. This is well-documented by the seminal study of Autor et al. (2013), which documents that the greater imports of manufactured goods from China into the U.S. reduce the local wages of the manufacturing sector. With its long history of protecting the domestic agricultural market, a study of South Korea provides an opportunity to investigate the impact of greater imports on individual farm outcomes. While the negative impacts on domestic producers from increased imports from foreign markets, with a comparative advantage, are expected and documented, there is limited evidence specifically addressing agriculture and the capacity of agricultural producers to adjust. Globally and historically, many countries have protected agriculture and the prospect of the sector with globalization and world market integration has been a great concern among policymakers. This paper intends to provide useful policy insights in this context.

The Korea-Chile FTA, which is the first major trade agreement that allowed foreign agricultural products to enter the South Korean domestic market, created an opportunity for Chilean fruits to be imported into South Korea. Thus, we examine the economic impacts of the increase in imports of fruits from Chile on farms in South Korea. We then model

[1] As of April 2024, South Korea has established 21 Free Trade Agreements (FTAs) with 59 countries. Beginning with the enforcement of the Korea-Chile FTA in 2004, many FTAs have been enforced with various partners, including Singapore, the European Free Trade Association (fully enforced in 2006), ASEAN (2009), India (2010), the European Union and Peru (2011), the United States (2012), Turkey (2013), Australia (2014), Canada, China, New Zealand, and Vietnam (2015), Colombia (2016), Central America, the United Kingdom (2021), RCEP, Israel, Cambodia (2022), and Indonesia (2023).

[2] Long-term effects would be an important topic to study, yet we refrain from studying the long-term effects as the farm-level data only track farms within a 5-year block. See the data section for the details.

and explore the differential impacts of the greater import exposure to provide some insights on whether larger and smaller farms react differently to the negative shocks and discuss the presence (or lack) of the adjustment and reallocation within firms that are exposed to greater shocks.

The direct estimation of how the increased imports affect farm revenue provides two important implications. First, a credible quantification of the causal effect can help policymakers assess the economic gains and losses from FTAs. We provide useful estimates on possible losses to farms as a result of the increased imports. Second, by investigating whether the increased imports reduce farm revenue and profit and how the impacts differ across the scales of operations, we can assess the ability of the farms to mitigate the trade shock. For example, farms would be reallocating their resources to more profitable crops or differentiating their products from imported products.

Overall, we find that the greater exposure to imports reduces farm revenue and profit. We observe that the negative effects are greater for the high-revenue farms. We attribute this to the possibility of the absence of immediate adjustment by examining the differential impacts of the import exposure on the share of fruits and vegetables in their total revenue. Our empirical findings imply that the farms with greater total revenue, who are likely to have greater shares of fruits and vegetables in their portfolios, experience greater absolute reductions in their revenue and profit as a response to the greater import exposure due to the absence of the immediate adjustment of their crop portfolios.

With the increase in regional or bilateral trade agreements around the world, the effects of trade agreements have been under consideration as an important topic of international trade. Trade agreements have been known to boost economic productivity (e.g., Benz and Yalcin, 2015), and the trade creation and diversion effects of trade agreements have been well-documented across industries, including agriculture (e.g., Burfisher et al., 2001; Chi et al., 2022; Freund, 2000; Grant and Lambert, 2008; Jean and Bureau, 2016; Koo et al., 2006; Lambert and McKoy, 2009; Luckstead, 2022; Magee, 2008; Miljkovic and Paul, 2003; Sun and Reed, 2010; Susanto et al., 2007). These studies find evidence that trade agreements positively affect the member countries' trade volume, which implies more exports and revenues. Although these studies find evidence that trade agreements positively affect the trade volume among the member countries, the estimates demonstrate the economic impacts at the macro-level.

More recent attention has focused on the effect of increasing trade with low-wage countries, such as China, on the local labor markets, presenting the negative impacts of import shocks from China on the local labor market of the U.S. (e.g., Acemoglu et al., 2016; Autor et al., 2013; Feenstra and Sasahara, 2018), Brazil (e.g., Costa et al., 2016; Dix-Carneiro and Kovak, 2017), and South Korea (e.g., Choi and Xu, 2020). In addition to the trade effect on manufacturing employment, this trend has also continued in the agricultural sector. For example, He (2020) analyzes how U.S. agricultural exports affect farm and nonfarm employment and confirms that there is a significant negative correlation between agricultural imports and farm employment in the U.S.

While the studies on the impacts of trade liberalization on the local labor market provide empirical evidence that is consistent with the negative (positive) effects of greater imports (exports) on the profitability of the industry, the literature on the direct micro-level estimation of the immediate effect of greater trade on income and profitability is relatively thin (Feler and Senses, 2017; Hakobyan and McLaren, 2016) and more so in agriculture. A notable exception is Yu et al. (2022). Yu et al. (2022) show that better access to foreign markets improves U.S. farm income related to farmland rent using a measure of localized tariff reduction. They find that the U.S. farmland rent increases about 3%–6% as the localized tariff decreases by one percentage point. Despite the evidence for the effects of export exposure on income, the impacts are still limited to farmland owners, not overall farm operators.

Meanwhile, more import exposure causes output prices to fluctuate, and then farms might respond to such price changes differently along their size due to the difference in supply elasticities (Adelaja, 1991; Mills and Schumann, 1985; Quiroga and Bravo-Ureta, 1992). In the short run, farms' behavior depends on their capital/labor intensity and ability to adjust costs in response to a price change. Specifically, the empirical studies on supply elasticities by firms' size suggest that large firms have stable output levels, while small firms have flexibility in production (Mills and Schumann, 1985). Kumbhakar (1993) finds that small farms tend to be less profitable compared to medium and large farms because small farms are less efficient. The empirical evidence indicates that farm size might matter when understanding and examining the effects of trade exposure on farm profitability.

This paper aims to estimate the impacts of the Korea-Chile FTA on agricultural profitability along with the distribution of farm size using a measure of individualized import exposure with farm-level data. The profitability of farmers may decrease as import exposure increases, while farmers may adjust their crop choices to respond to import shocks. To capture the heterogeneous effects of import exposure on the entire distribution of farm revenue, we utilize the unconditional quantile regression (UQR) approach. We contribute to the literature on the linkage between trade exposure and farm profitability by directly measuring import exposure to individual farms and explaining the heterogeneous effects of trade on farms.

## 4.2 Background: Korea-Chile Free Trade Agreement

Over the past two decades, the farm economy in South Korea has been perceived as a diminishing sector. Rapid economic growth led to a decrease in the share of the agricultural sector in GDP. Moreover, decreasing and aging in the farm household population has increased the burden of labor costs to produce agricultural products. In addition, South Korea is a net importer in the global agricultural market, and thus, many trade agreements increase the pressure from imports of agricultural products. Figure 4.1 displays the trend in the annual agricultural imports of South Korea from the world. Both total agricultural imports and imports of fruits have been increasing from 2002 to 2020.

The Korea-Chile FTA is the first FTA for South Korea. South Korea and Chile began to negotiate the FTA in 1999 and the agreement entered into force in April 2004 (Ministry of Trade, Industry and Energy (MOTIE), 2024). They held 6 rounds of negotiations; the first round of negotiation took place in Santiago on December 14–17, 1999, and the negotiation ended in Geneva on October 18–20, 2002. The Korea-Chile FTA was signed on February 15, 2003. The Chilean Senate approved the agreement and completed legislative procedures

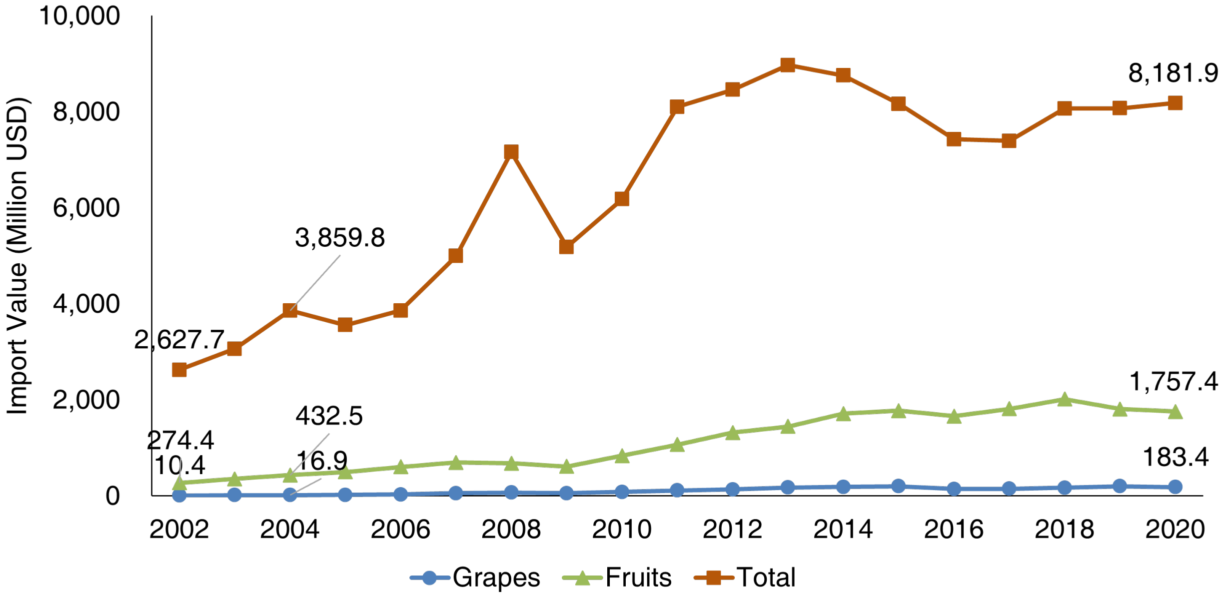


Figure 4.1: South Korea's annual agricultural imports from the world (2002–2020)

on January 22, 2004, and the Korean Parliament approved it on February 16, 2004. After approval of the agreement, the Korea-Chile FTA entered into force on April 1, 2004.

In the tariff schedule of Korea, 21 agricultural commodities, including rice, apples, and pears, were excluded from the tariff elimination and both governments agreed to discuss the elimination of tariffs on 373 other sensitive commodities, such as garlic, onions, peppers, powdered milk, and oranges, after the Doha Development Agenda negotiations of the WTO. Fresh grapes are one of the most sensitive agricultural products in Korea. In consideration of the grape growing seasons in Korea, it was agreed to eliminate tariffs evenly on fresh grapes imported from November 1 to April 30 and apply seasonal tariffs that maintain the current Most-favored-nation (MFN) tariffs for the rest of the import period.

One of South Korea's major agricultural products imported from Chile is fresh grapes. In figure 4.2, since the Korea-Chile FTA entered into force in 2004, the imports of fresh grapes from Chile to Korea have increased from \$13.1 million in 2003 to \$74.3 million in 2020 (World Bank, 2024). Figure 4.3 presents the domestic price index of fruits and vegetables, which shows some immediate price declines after the enforcement of the agreement. However, it is unclear whether there has been a significant structural change in price movements.

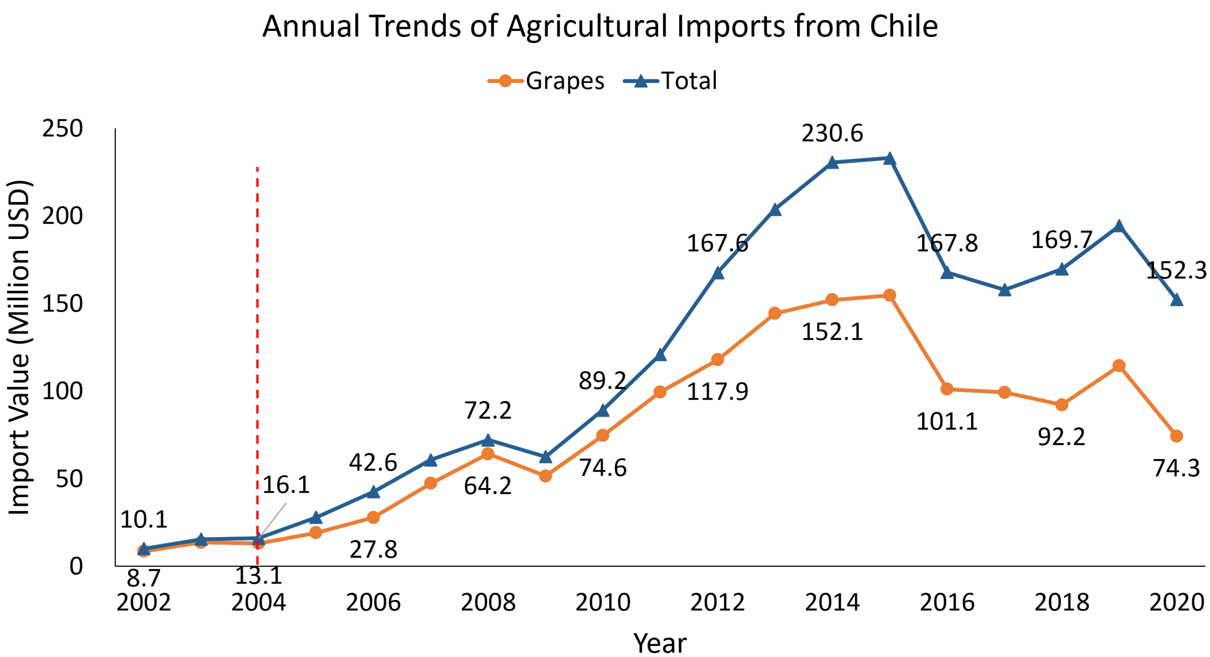


Figure 4.2: South Korea's annual agricultural imports from Chile (2002–2020)

## 4.3 Data and variable construction

Our primary data source is Farm Household Economy Survey (FHES) of South Korea.[3] Statistics Korea conducts FHES, an annual survey on the economy of 3,200 sampled farm households in administrative districts for the calendar year. FHES data provides information on farm businesses and households, such as returns, costs, assets, liabilities, farm size, and the types of agricultural commodities that farms produce.[4]

The target population for FHES is all farm households who cultivated more than 1,000 square meters (roughly 0.25 acres) of land or whose annual agricultural sales were more than 500,000 Korean won (KRW), roughly 416 U.S. dollars (USD) in 2000.[5][6] The FHES uses a sample frame derived from the population of the Census of Agriculture in 2000 and divides the population into sub-groups known as strata by farm commodity specialization. After stratification, samples are selected based on the probability proportional to size (PPS)

[3]For the additional empirical studies using the FHES data, see Kim et al. (2012) and Kim et al. (2014).

[4]The types of agricultural commodities are rice, wheat, mixed grain, pulses, potatoes, vegetable, fruits, floriculture crops, specialty crops, and agricultural byproducts.

[5]The definition of the target population for FHES is based on the Census of Agriculture in 2000.

[6]We exchange KRW to USD using 1 USD = 1,200 KRW for enhanced understanding.

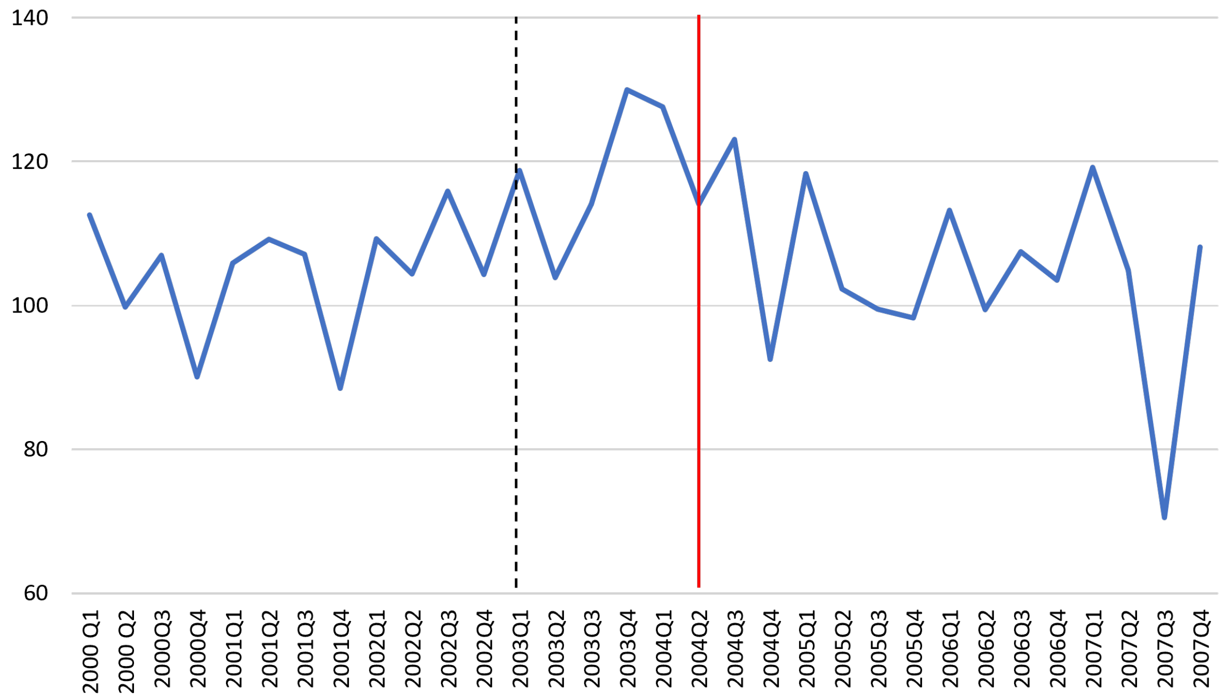


Figure 4.3: Fruits and vegetables price received index (2005 = 100)

Note: Statistics Korea provides the price index of farm products received by farms. A price index is constructed using administrative data provided by Nonghyup, the South Korean National Agricultural Cooperative Federation. In order to calculate the price index, the Laspeyres formula is used with weights derived from recent farm cash receipts (Source: Statistics Korea (2021)). The Black dashed line and red solid line denote the sample period starts and the year the Korea-Chile FTA entered into force, respectively.

sampling within the strata.

Since the samples are derived from the Census of Agriculture, which is conducted by Statistics Korea every five years, the FHES samples and identifiers change every five years. In other words, we can only track farms for each Census period (e.g., 2003–2007, 2008–2012, and so on) as the identifiers uniquely identify farms only within a Census period. Therefore, we use the 2003–2007 sample so that we have information for both pre-FTA (2003–2004) and post-FTA (2005–2007). In addition, the FHES provides sampling weights, so we utilize the provided survey weights in our regression analysis to account for the survey design and ensure that our estimates represent the population.

Data on the import values of fruits and vegetables are from the World Integrated Trade Solution (WITS) database that provides access to the United Nations Statistical Division Commodity Trade (UN Comtrade). We extract the data on the value of imported fruits and vegetables to Korea using the 6-digit Harmonized Tariff Schedule (HS) code from 2003 to 2007.[7]

Our main dependent variables are crop revenue, farm profit, and labor cost.[8] Crop revenue in FHES is defined as the sum of sales revenue, the values of self-consumption, and inventory.[9] Crop revenue is a measure of the end-of-year return from crop production of the sample farms, which is the result of production decisions, weather, and market conditions. We argue that the crop revenue variable is an appropriate measure to assess the immediate and composite effect of greater exposure to agricultural imports from foreign countries.

Recent studies show that increasing imports negatively affect local labor markets and the profitability of the producers (Autor et al., 2013; Dix-Carneiro and Kovak, 2017). Hence, in addition to crop revenue, we also consider farm profit and labor cost as our dependent variables. Farm profit is defined as crop revenue minus farm operating costs which are costs for production inputs (e.g., seed, fertilizer, chemicals, feed), labor cost, overhead cost (e.g., maintenance and repair of farm buildings, farm utilities, farm supplies, marketing containers, rental costs, interest on operating capital, taxes, etc.), and depreciation cost for farm fixed asset. Lastly, labor cost is defined as the amount paid for hired or family labor.

Our explanatory variable of interest is individualized import exposure, which is a measure of how much import exposure that individual farms are subject to. The key challenge is to construct an individualized variable from national-level fruits and vegetable imports from Chile. Motivated by Autor et al. (2013), we compute the individualized import by the following equation:

[7]We compile the 6-digit HS codes into commonly used agricultural commodity groupings following the standard from Korea Agro-Fisheries & Food Trade Corporation (aT). The list of commodities imported from Chile to South Korea in 2003–2007 is 070310 (alliaceous vegetables, fresh), 070920 (asparagus), 071080 (vegetables, frozen), 071290 (dried vegetable), 080510 (orange), 080550 (lemon), 080610 (grapes), 081050 (kiwifruit), 081110 (strawberry), 081190 (other fruits and nuts), 081340 (other fruits), 090420 (pepper), and 121190 (plants and parts (including seeds and fruits)).

[8]As FHES does not collect more detailed information on farm economy (e.g., price or quantity of crop, the amount of inventory, etc.), we believe these are the most appropriate outcome variables of interest that reflect farm profitability and farm economy.

[9]Crop revenue may be negative due to the value of inventory. For example, if the value of inventory is decreased or the losses from it are higher than the production of the farm, then crop revenue for the farm is considered negative due to the reduction in its inventory.

$$Import_{it} = \frac{Revenue_{i,pre}^{F\&V}}{Total\ Revenue_{pre}^{F\&V}} \times Import_t^{F\&V} \tag{4.1}$$

where $Total\ Revenue_{pre}^{F\&V}$ denotes the average of national-level total crop revenue from fruits and vegetable sales in 2003–2004, $Revenue_{i,pre}^{F\&V}$ is the average fruits and vegetables revenue for farm $i$ in 2003–2004, and $Import_t^{F\&V}$ is the import value of fruits and vegetables from Chile in year $t$ where $t = \{2004, 2005, 2006, 2007\}$. We also consider computing $\frac{Revenue_{i,pre}^{F\&V}}{Total\ Revenue_{pre}^{F\&V}}$ of equation 4.1 using the sampling weight and report the results in Appendix C. The overall finding remains robust.

The FHES only breaks down the crop revenue by broad groups of agricultural commodities the farm produced. To match the import values from WITS and the crop revenues of FHES, we aggregate the import values of the HS codes and define the aggregated values as fruits and vegetables. Similarly, we also aggregate the revenues from the two groups, fruits and vegetables, to have the aggregated crop revenue from fruits and vegetables productions. All import values are exchanged for KRW and adjusted to 2003 KRW using the exchange rate and the consumer price index (Bank of Korea, 2022) to calculate an individualized import variable for analysis. In addition, values in FHES are also deflated to 2003 KRW.

Finally, we restrict our samples to the farms that appeared in 2003 to capture the effect of both pre- and post-FTA. Also, as we use 2003–2004 averages to compute equation 4.1, we restrict the sample periods to the years 2004–2007. We present the results from the analyses for the years 2003–2007 in Appendix C, and the results remain robust. We further restrict our sample to farms with any non-negative value of farm receipts in the samples to avoid the inclusion of the effects derived from the inventory reduction. We also examine the robustness with respect to the exclusion of the farms with negative farm receipts and present the results in Appendix C and observe similar robust results. For the final sample, we have a total of 5,251 farm-by-year observations.

Table 4.1 reports the descriptive statistics for the key variables for the overall sample and the subsamples of 2004–2007. In general, key variables vary considerably across farms except for the fruits and vegetables share, as shown by the greater standard deviations than the mean. From 2004 to 2007, the total crop revenue decreased from 22 million real KRW (18,400 USD) to 20.8 million real KRW (17,300 USD). On the other hand, the total farm profit increased from 927 thousand real KRW (773 USD) to 1,025 thousand real KRW (854 USD). The individualized import exposure computed by equation 4.1 also increased continuously, with imports from Chile increasing by almost double over the same period.

Table 4.1: Descriptive statistics of farm-level observations by year

| VARIABLES | 2004–2007 Average | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|
| Total Crop Revenue | 20.82 | 22.10 | 20.30 | 20.44 | 20.07 |
| (million 2003 KRW) | (26.78) | (27.59) | (27.24) | (25.07) | (26.82) |
| Total Farm Profit | 12.04 | 13.11 | 12.64 | 11.86 | 10.19 |
| (million 2003 KRW) | (18.52) | (19.76) | (20.24) | (16.04) | (17.10) |
| Total Labor Cost | 0.96 | 0.93 | 0.97 | 0.91 | 1.03 |
| (million 2003 KRW) | (3.41) | (2.78) | (3.94) | (3.25) | (3.72) |
| Share of Fruits and Vegetables | 0.414 | 0.407 | 0.406 | 0.410 | 0.436 |
| (%) | (0.336) | (0.339) | (0.331) | (0.338) | (0.333) |
| Fruit & Vegetables Import Exposure | 14.69 | 8.23 | 11.87 | 16.84 | 23.92 |
| (Chile, million 2003 KRW) | (30.04) | (15.24) | (22.01) | (30.80) | (44.86) |
| No. of Observations | 5,251 | 1,592 | 1,250 | 1,192 | 1,217 |

Note: Standard deviations are in parentheses. One million KRW $\approx$ 0.8 thousand USD.

Figure 4.4 shows the kernel distribution of the real total crop revenue in 2004–2007. The distribution is skewed to the right, with a spike at 13,400 thousand 2003 KRW in 2004 and at 11,200 thousand 2003 KRW in the rest of the years, and the variance of the dependent variable is largest in 2004. On top of that, there is a tendency for the distribution of the dependent variable to increase along with its level as the real total crop revenue increases. Similar skewed distributions are observed for farm profit and labor cost.

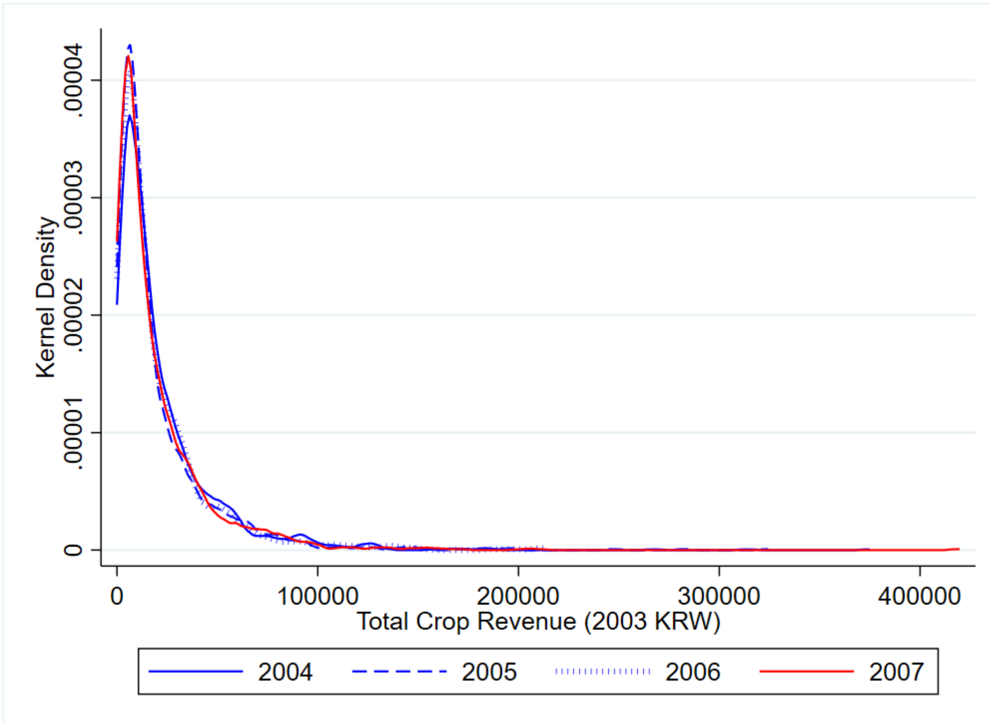

Figure 4.4: The Kernel density estimation of crop revenue (2003 KRW)

## 4.4 Empirical approaches

To estimate how the increased imports affect individual farm economies, we consider the following estimation equation:

$$y_{it} = \beta_0 + \beta_1 Import_{it} + X'_{it}\Gamma + u_i + v_{st} + \epsilon_{it} \tag{4.2}$$

where $y_{it}$ indicates the dependent variables, which are the crop revenue, farm profit, and labor cost, for farm $i$ in year $t$,[10] $Import_{it}$ is individualized import for farm $i$ from Chile defined by equation 4.1, $X'_{it}$ is a vector containing control variables for farm characteristics, which are non-farm income, agricultural subsidy, types of farming, indicators of full-time farm and part-time farm, types of business, farm acres, age of farm operator, number of farm household members, educational attainment of farm operator for farm $i$ in year $t$,

[10]As the dependent variables have wide ranges of their scale, we also consider transforming them with Inverse Hyperbolic Sine transformation. The results are reported in Appendix C and do not change with the transformation.

and $u_i$ and $v_{st}$ are farm and province-by-year fixed effects to control for unobservable time-invariant effects and time-variant shocks that affect overall farm production. Standard errors are clustered by province and by year to control for possible correlations within province and year (Cameron et al., 2011) and samples are weighted by the sampling weight.[11]

In equation 4.2, $\beta_1$ identifies the effect of rising imports on the individual fruits and vegetable farm economy. Although all farm households face the same national shock, the import value and the initial revenue share for the farm $i$, $\frac{Revenue^{F\&V}_{i,pre}}{Total\ Revenue^{F\&V}_{pre}}$, provide cross-sectional variations in the import exposure. The shift-share design literature (e.g., Autor et al., 2013; Bartik, 1991; Goldsmith-Pinkham et al., 2020) provides a useful framework for constructing import exposure variables that can tackle their possible endogeneity issues. Goldsmith-Pinkham et al. (2020) shows the consistency condition based on a large number of cross-sectional units, which is the exogeneity of the share conditional on fixed effects and the covariates.

This consistency condition applies to our case as we have a relatively large number of cross-sectional units (e.g., farms) in our sample. Therefore, our identification hinges on the conditional exogeneity of the share, $\frac{Revenue^{F\&V}_{i,pre}}{Total\ Revenue^{F\&V}_{pre}}$, conditional on farm and year fixed effects and the covariates. That is, as long as there is no specific channel between the pre-FTA share of a farm in national food and vegetable revenue and the farm outcomes conditional on fixed effects and covariates, the identification is viable. We do not believe that there are unobservable time-varying factors that are correlated with the pre-FTA share and the revenue changes once we control for farm fixed effects and other observable covariates.

Quantile regression, pioneered by Koenker and Hallock (2001), provides robust estimates of the coefficient of the interest with respect to the distributional assumptions. As we see in figure 4.4, crop revenue has a skewed distribution and it is important to capture possible heterogeneity in the effect across the quintile. The quantile approach can provide useful insights into the distributional impact of the import exposure as it allows us to estimate the effect of the import exposure by quantile.

[11] Following an anonymous reviewer's suggestion, we also estimate the standard errors using weighted Jackknife estimation. The results remain similar and are reported in Appendix C.

Consistent with our linear model specification, represented by equation 4.2, we need to control for farm and province-by-year fixed effects. Hence, we consider the following conditional quantiles:

$$Q_y(\tau|X) = \beta_0(\tau) + \beta_1(\tau)Import_{it} + u(\tau)_i + v(\tau)_t \tag{4.3}$$

where $Q_y(\tau|X)$ is the conditional $\tau$-th quantile of $y$ whose distribution is conditional on the given covariate vector $X$, which includes the individualized import value ($Import_{it}$), farm and province-by-year fixed effects.

The estimates of the conditional quantile regressions (CQR) provide the effect of changes in the explanatory variable within-group dispersion, where the group indicates the farms that have the same values of the covariates other than the import exposure (Firpo et al., 2009). However, the estimated coefficients of the CQR do not show the influence of increasing import exposure on the overall farm economy, but can be interpreted as the marginal effect on the conditional mean. Therefore, we estimate the unconditional quantile regressions (UQR), that offer both within- and between-group effects of the import exposure. Moreover, the advantage of UQR is the inclusion of fixed effects (covariates) on the regression does not affect the quantile of the dependent variable.

We follow the approach of Firpo et al. (2009) to estimate the marginal effect of the import exposure on the unconditional quantiles of the dependent variables. Using the recentered influence function (RIF), the effect of import exposure on the marginal (unconditional) quantiles of the dependent variable can be captured by estimating the following equation:

$$RIF(y_{it}; q_\tau, F_y) = \beta_0 + \beta_1 Import_{it} + u_i + v_t + \epsilon_{it} \tag{4.4}$$

where $y_{it}$ are the crop revenue, farm profit, and labor cost, $q_\tau$ is the $\tau$-th quantile of $y$, $F_y$ is the cumulative density function of $y$, and

$$RIF(y_{it}; q_\tau, F_y) = q_\tau + \frac{\tau - I\{y \leq q_\tau\}}{f_y(q_\tau)} \tag{4.5}$$

with $I\{y \leq q_\tau\}$ is a dummy variable that indicates 1 if the value of $y$ is less than the value of $y$ at $q_\tau$, and $f_y(q_\tau)$ is the probability density function for $y$ evaluated at $q_\tau$. Equation 4.4 can be estimated by OLS using the definition of equation 4.5 for the dependent variable with the assumption that $Pr[Y > q_\tau | X = x]$ is linear in $x$, where $X$ is the vector of covariates.

## 4.5 Results

As we discussed, our objective is to estimate the average and distributional effects of import exposure on the farm economy. The average effects are estimated via equation 4.1, and the distributional effects are estimated by the UQR approach (equation 4.4), i.e., differential effects across quantiles.

Table 4.2 provides the estimates of equation 4.2 with different dependent variables. Columns (1) and (2), Columns (3) and (4), and Columns (5) and (6) are the results with crop revenue, farm profit, and labor cost as the dependent variables. Columns (1), (3), and (5) report the models only with farm fixed effects and province-by-year fixed effects, whereas Columns (2), (4), and (6) present the estimates with the set of control variables.

Table 4.2: Average effects of fruits and vegetable import exposure from Chile on farm economy

| VARIABLES | (1) Crop Revenue (2003 million KRW) | (2) | (3) Farm Profit (2003 million KRW) | (4) | (5) Labor Cost (2003 million KRW) | (6) |
|---|---|---|---|---|---|---|
| F & V Import – Chile | -0.0285 | -0.0562*** | -0.0351* | -0.0593** | 0.0056 | 0.0057 |
| (2003 million KRW) | (0.0186) | (0.0198) | (0.0195) | (0.0246) | (0.0059) | (0.0059) |
| Observations | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. * Significant at the 10 percent level; ** Significant at the 5 percent level; *** Significant at the 1 percent level.

Overall, the effects on crop revenue and farm profit of the imports from Chile are negative, while we do not see any significant impacts on labor costs. The magnitudes of coefficients for crop revenue and farm profit increase when the additional control variables[12] are included in the regression. Yet, the direction of the effects remains robust between the specifications with and without the additional controls. Our empirical evidence suggests that a unit increase in the individualized import value reduced 29,000 KRW to 56,000 KRW of crop revenue for fruits and vegetable farms on average. When converting the unit to the average value using the average change in table 4.1, individual farms that produce fruits and vegetables experienced 0.1 to 0.2 million KRW (roughly 800–1,600 USD) reductions in crop revenue as the individualized import value increased by 3.6 million KRW, which is the average change between 2004 and 2005 reported in table 4.1.

The results of UQR estimation are summarized in table 4.3 and figure 4.5. In table 4.3, columns (1)–(3) report the estimates of the three dependent variables, crop revenue, farm profit, and labor cost, for 0.25, 0.50, and 0.75 quantiles (i.e., the conditional $\tau$-th quantile, $Q_y(\tau|X)$, for $\tau$=0.25,0.5,0.75). Comparing the three columns, we observe substantial heterogeneity in the effects of the import exposure for all three dependent variables. Columns (1) and (2) show that the effects of the import exposure are small or negligible for smaller quantiles, whereas significant and greater negative effects are observed for the 75th quantile.

Figure 4.5 provides a more complete picture of the heterogeneous effects of FTA on the farm economy by presenting estimated coefficients of UQR from the 10th to the 90th quantile. A noticeable observation is that the detrimental effects on crop revenue and farm profit are greater for the higher quantiles. Particularly, negative and significant effects are observed for the quintiles greater than the 60th quantile. That is, farms at the top of the crop revenue distribution reduced their crop revenue more than those at the bottom and middle of the distribution. We also see the effects are close to zero for the farms located in lower quintiles. Consistent with table 4.3, the effect on labor cost remains to be close to zero.

With fruits and vegetables being high-valued commodities compared to other commodities grown in South Korea (e.g., rice), farms with greater quantiles in terms of crop revenue

[12] The list of control variables includes non-farm income, agricultural subsidy, types of farming, indicator of full-time farm and part-time farm, types of business, farm acres, age of farm operator, number of farm household members, and educational attainment of farm operator.

Table 4.3: UQR: Effects of import exposure from Chile on farm economy by quantile

| VARIABLES | (1)<br>$\tau = .25$ | (2)<br>$\tau = .50$ | (3)<br>$\tau = .75$ |
|---|---|---|---|
| *Dependent variable: Crop revenue* | | | |
| F & V Import – Chile | -0.0025 | -0.0176 | -0.1204*** |
| | (0.0079) | (0.0111) | (0.0279) |
| *Dependent variable: Farm profit* | | | |
| F & V Import – Chile | 0.0140*** | 0.0039 | -0.0965*** |
| | (0.0048) | (0.0064) | (0.0311) |
| *Dependent variable: Labor cost* | | | |
| F & V Import – Chile | 0.000149 | 0.000032 | -0.004468** |
| | (0.000155) | (0.000160) | (0.002137) |
| Observations | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes |

Note: All regressions include a constant and the control variables. Both dependent and key independent variables are in 2003 million KRW. Cluster-robust standard errors are clustered by province and year and reported in parentheses. * Significant at the 10 percent level; ** Significant at the 5 percent level; *** Significant at the 1 percent level.

are likely to have larger shares of fruits and vegetables in their total crop revenue. Figure 4.6 shows the positive correlation between the share of fruits and vegetables and total crop revenue using a binned scatter plot. That is, the absorbed import shock is larger for the farms with higher revenues as their revenue depends more on the revenue from fruits and vegetables.

## 4.6 Changes in the share of fruits and vegetables

To shed light on potential mechanisms behind the effect of trade exposure on farm revenue and profit, we further investigate the effects of exposure to increased imports on the share of fruits and vegetables in total crop revenue. To do so, we estimate

$$Share\ of\ F\ \&\ V_{it} = \gamma_0 + \gamma_1 Import_{it} + X_{it}'\Theta + u_i + v_{st} + \epsilon_{it} \tag{4.6}$$

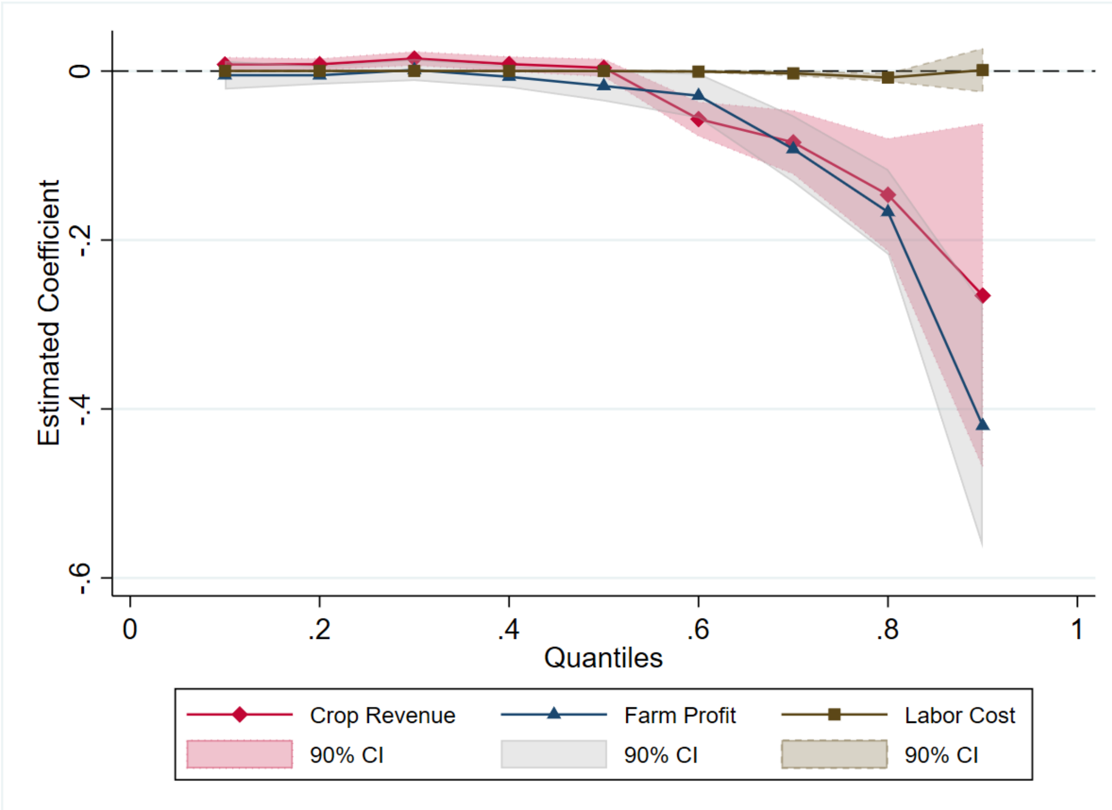


Figure 4.5: UQR estimates of the effect of imports from Chile on farm economy
Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

where $Share\ of\ F\ \&\ V_{it}$ is the shares of the receipts from fruits and vegetables sales over the total crop revenue for farm $i$ in year $t$, $X'_{it}$ is a vector for control variables including non-farm income, agricultural subsidy, types of farming, an indicator of full-time farm and part-time farm, types of business, farm acres, age of farm operator, number of farm household members, educational attainment of farm operator, $u_i$ is a farm fixed effect, and $v_{st}$ is a province-by-year fixed effect. We estimate equation 4.6 and its UQR specification.

We focus on the results of the UQR estimation as it can provide suggestive evidence on the presence of adjustment via reallocation of the crops. Assuming no immediate adjustment, consider the following simple representation of the share of fruits and vegetables over the total revenue before the import shock:

$$Share\ of\ F\ \&V_{pre} = \frac{F\ \&\ V\ Revenue_{pre}}{F\ \&\ V\ Revenue_{pre} + Other\ Crop\ Revenue_{pre}}$$

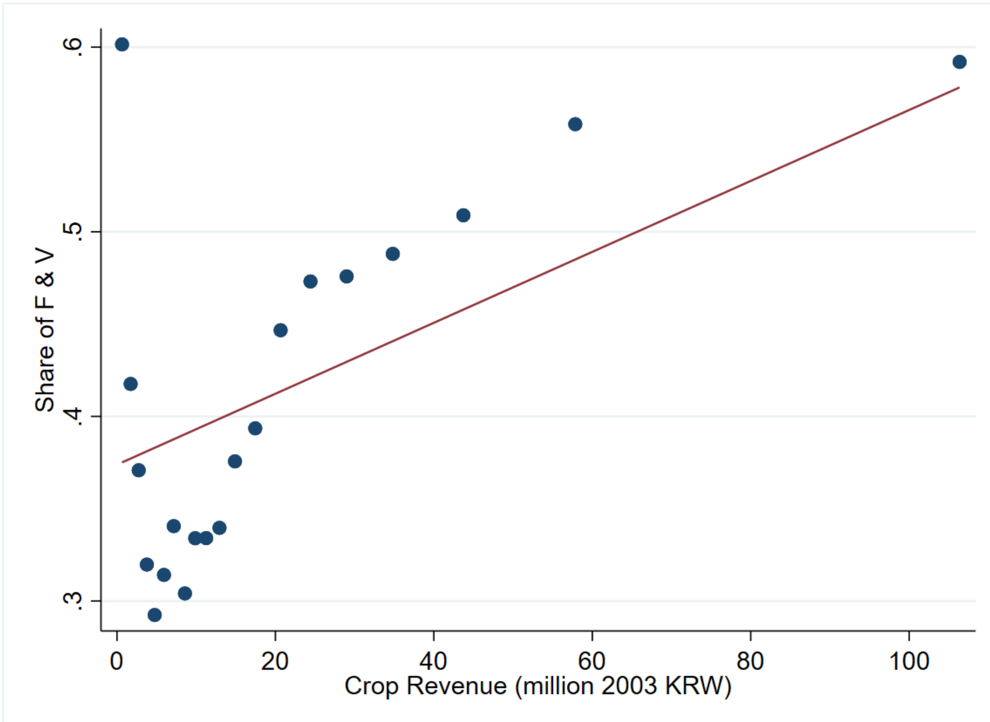


Figure 4.6: Binned scatter plot between the share of fruits and vegetables and total crop revenue

Then, we can write the post-shock share without any adjustment, where $0 < Shock < 1$ as

$$Share\ of\ F\ \&V_{post} = \frac{F\ \&\ V\ Revenue_{pre} \times (1 - Shock)}{F\ \&\ V\ Revenue_{pre} \times (1 - Shock) + Other\ Crop\ Revenue_{pre}}$$

which can be further rewritten as the function of $Share\ of\ F\ \&V_{pre}$:

$$Share\ of\ F\ \&V_{post} = \frac{Share\ of\ F\ \&V_{pre} \times (1 - Shock)}{1 - Share\ of\ F\ \&V_{pre} \times Shock}. \tag{4.7}$$

To visualize the relationship between the change in the share of fruits and vegetables before and after the shock and the initial share of fruits and vegetables, we present a numerical example in figure 4.7. The numerical example in figure 4.7 considers the shocks ranging from 10 to 30 percent reduction in the revenue from fruits and vegetables while holding others constant. We observe a U-shape relationship as the farms with lower or higher ends of the share of fruits and vegetables before the shock does not experience much change in

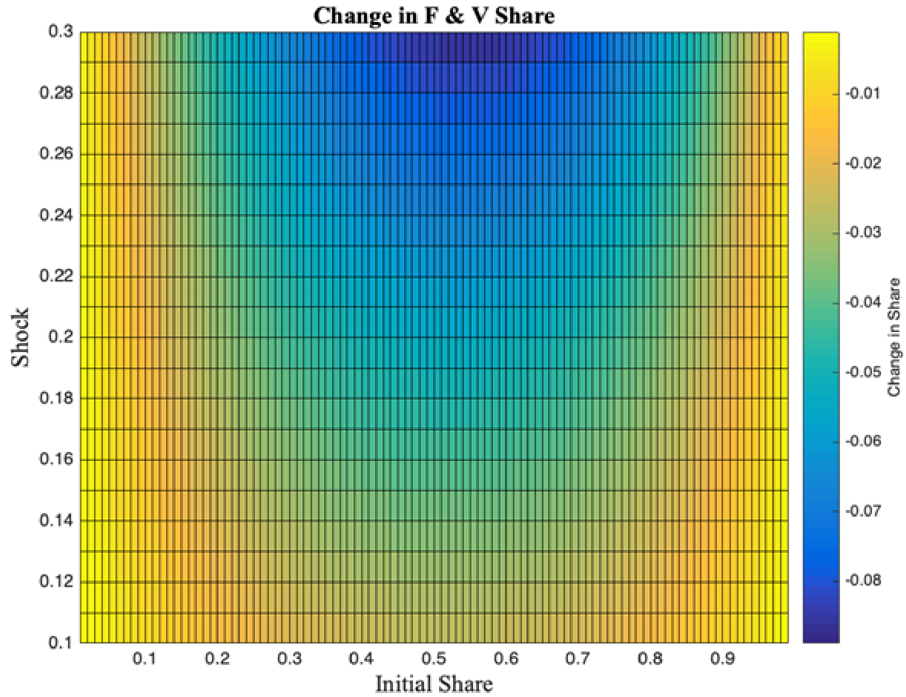


Figure 4.7: Numerical illustration of the relationship between the changes in the share of fruits and vegetables after shock and the initial share of fruits and vegetables
Note: The changes in share are computed by taking the difference between equation 4.7 and the initial share of fruits and vegetables.

the share regardless of the size of the shocks. The difference between the middle group and the lower and higher groups becomes apparent when the shock gets greater. Again, this is to highlight the effect of the price reduction in fruits and vegetables when there is no possibility of adjusting the production portfolio.

In table 4.4, we present the estimates of OLS and UQR specification of equation 4.6. Overall, we find that the share of fruits and vegetables decreases as the import exposure increases with the heterogeneity across quantiles. Figure 8 presents the estimates across the quantiles from the 10th to the 90th. Interestingly, we find that significant and negative effects are among the lower quantiles and the effects are less negative and more imprecise for the higher quantiles.

The findings from table 4.4 and figure 4.8 can be the results of i) reductions in the fruits and vegetables revenue due to price declines or ii) reallocations of crops within farms. Without any reallocation or adjustments in which crops to produce, the effect of the import

Table 4.4: Effects of import exposure from Chile on the share of fruits and vegetables

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | $(Share\ of\ Fruits\ \&\ Vegetables) \times 100$ | | | | |
| | OLS | | UGR | | |
| VARIABLES | | | $\tau = .25$ | $\tau = .50$ | $\tau = .75$ |
| F & V Import – Chile | -0.0384*** | -0.0335** | -0.0420*** | -0.0665* | -0.0474 |
| (2003 million KRW) | (0.0140) | (0.0139) | (0.0140) | (0.0371) | (0.0365) |
| Observations | 4,837 | 4,837 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | Yes | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. * Significant at the 10 percent level; ** Significant at the 5 percent level; *** Significant at the 1 percent level.

exposure, presumably through the decline in prices, on the share of the revenue from fruits and vegetables would follow a pattern that is similar to the illustration in figure 4.7. Quantiles from the 10th to the 60th in figure 4.8 show a similar U-shape pattern that is consistent with the numerical illustration in figure 4.7. The higher quantiles, 70th – 90th, show an estimated effect that is close to zero (with the exception of the positive effect for the 80th quantile).

While the UQR estimation results do not provide direct evidence on the absence of the adjustment, we can deduce that the degree of adjustment as responses to the negative shocks from more import is limited by comparing figures 4.7 and 4.8. We also can infer that the farms with higher revenues (who are likely to have greater shares of their revenue from fruits and vegetables as represented in figure 4.6) are not more flexible than the smaller farms as reflected in the non-negative responses to the import shocks in figure 4.8. This is plausibly due to the dynamic nature of perennial crops and the adjustment costs.

## 4.7 Conclusion

An increase in regional or bilateral free trade agreements around the world has contributed to greater trade volumes among the countries in the agreements. Recent studies find that

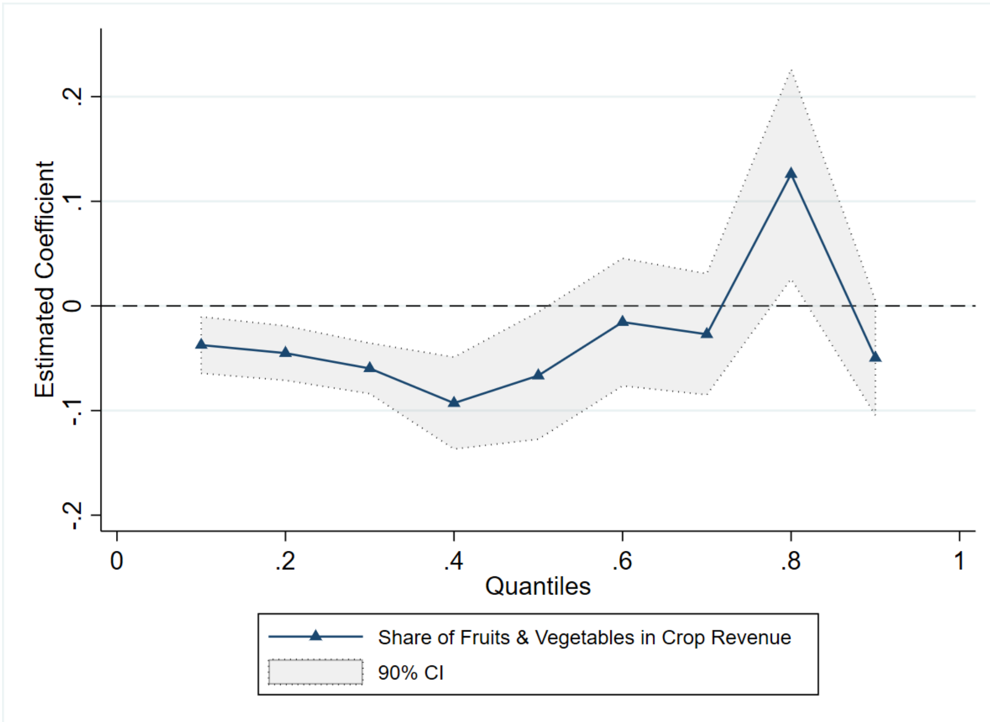


Figure 4.8: UQR estimates of the effect of imports from Chile on the share of fruits and vegetables
Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

greater imports affect the labor market, especially wages or employment, resulting in less profitability for the industry. Although extensive research has shown the economic impact of trade agreements in the manufacturing sector, the empirical literature on how greater agricultural imports affect individual farms in importing countries is relatively thin.

We study the immediate impact of a free trade agreement on the farm economy of an importing country. South Korea serves as an experimental chamber because of its long history of protecting its domestic agricultural market. The agreement with Chile is the first major free trade agreement that relieved trade barriers for foreign agricultural products.[13] Hence, an empirical examination of the immediate impact of the agreement on individual farm outcomes can provide useful economic and policy insights on the consequences of globalization and trade liberalization for the producers in importing countries.

Using the comprehensive dataset on farm and import values by types of agricultural prod-

[13]We also estimate the impact of the import exposure using imports value from the world, which include imports from Chile, and find a similar result and report in Appendix C.

ucts from 2003 to 2007 and the individualized import shock, we find that greater exposure to imports reduced farm revenue and profit with greater negative effects for the high-revenue farms. The absence of immediate adjustment can be a plausible explanation as the adjustment costs are greater for fruits and vegetables production. Our empirical findings indicate that trade liberalization has substantial negative impacts on the producers in importing countries, and the adjustment is costly, at least in the immediate or short run. Further investigations of the long-run consequences can provide additional policy implications.

# Chapter 5

# Conclusion

With better accessibility to foreign markets, a country's agriculture may gain or lose from trade and the impact of trade can be heterogeneous by regional or individual agricultural backgrounds. The potential benefits are particularly pronounced for exporters, who experience significant tariff reductions as a result of trade liberalization. On the other hand, if individual farm operators lose their comparative advantage in producing and exporting, it would impact farm business decisions on input use, crop choice, or exit from the market. Hence, it becomes important to understand the impact of trade exposure on agricultural production and farm economy with a keen focus on identifying the heterogeneous effects by region or individual.

Chapter 2 examines the effects of localized trade shocks on crop acreage and yield, showing the effects are different across crops and across the short-, medium- and long-run. Chapter 3 explores the role of farm-level trade exposure, which reveals that it positively impacts farm profitability in the short term. However, these effects are reversed over the long term driven by factors beyond trade values. Moreover, the degree of trade exposure significantly influences the likelihood of farm survival, highlighting its critical role in shaping farm dynamics over time. Chapter 4 investigates how individual farms in importing countries respond to trade shocks. The results indicate that increased exposure to imports from countries that exhibit comparative advantage reduces farm revenue and profit with greater negative effects for the high-revenue farms. These findings emphasize the substantial adverse effects of trade liberalization on domestic producers in importing countries, particularly highlighting the challenges of nonflexible adjustments in fruit and vegetable production in the short term.

# Bibliography


Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics*, 34:S141–S198.

Adelaja, A. O. (1991). Price changes, supply elasticities, industry organization, and dairy output distribution. *American Journal of Agricultural Economics*, 73:89–102.

Adjemian, M. K., Smith, A., and He, W. (2021). Estimating the market effect of a trade war: The case of soybean tariffs. *Food Policy*, 105:102152.

Arora, G., Feng, H., Anderson, C. J., and Hennessy, D. A. (2020). Evidence of climate change impacts on crop comparative advantage and land use. *Agricultural Economics*, 51:221–236.

Autor, D. H., Dorn, D., and Hanson, G. (2013). The China syndrome: Local labor market effects of import competition in the United States. *The American Economic Review*, 103:2121–2168.

Baggs, J. (2005). Firm survival and exit in response to trade liberalization. *Canadian Journal of Economics*, 38:1364–1383.

Balassa, B. (1965). Trade liberalisation and “revealed” comparative advantage. *The Manchester School*, 33:99–123.

Bank of Korea (2022). Economic statistics system. https://ecos.bok.or.kr.

Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute.

Benz, S. and Yalcin, E. (2015). Productivity versus employment: Quantifying the economic effects of an EU–Japan Free Trade Agreement. *The World Economy*, 38:935–961.

Bontemps, C., Bouamra-Mechemache, Z., and Simioni, M. (2013). Quality labels and firm survival: Some first empirical evidence. *European Review of Agricultural Economics*, 40:413–439.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89:181–213.

Burfisher, M. E., Robinson, S., and Thierfelder, K. (2001). The impact of NAFTA on the United States. *Journal of Economic Perspectives*, 15:125–144.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, 8:106–140.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business and Economic Statistics*, 29:238–249.

Carter, C. and Steinbach, S. (2020). The impact of retaliatory tariffs on agricultural and food trade.

Chi, P., Chang, T., and Chang, K. (2022). Evaluating the impact of preferential trade agreement on fishery imports: An application of difference-in-differences with matching method. *Agricultural Economics*, 53:90–124.

Choi, J. and Xu, M. (2020). The labor market effects of the China syndrome: Evidence from South Korean manufacturing. *The World Economy*, 43:3039–3087.

Costa, F., Garred, J., and Pessoa, J. P. (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics*, 102:50–69.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 34:187–202.

Dix-Carneiro, R. and Kovak, B. K. (2017). Trade liberalization and regional dynamics. *The American Economic Review*, 107:2908–2946.

FAOSTAT (2024). Crops and livestock products. *Food and agriculture data.* https://www.fao.org/faostat/en/data/QCL.

Feenstra, R. C. and Sasahara, A. (2018). The 'China shock,' exports and U.S. employment: A global input–output analysis. *Review of International Economics*, 26:1053–1083.

Feler, L. and Senses, M. Z. (2017). Trade shocks and the provision of local public goods. *American Economic Journal: Economic Policy*, 9:101–143.

Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, 77:953–973.

Freund, C. (2000). Different paths to free trade: The gains from regionalism. *The Quarterly Journal of Economics*, 115:1317–1341.

Gardner, B. L. (1976). Futures prices in supply analysis. *American Journal of Agricultural Economics*, 58:81–84.

Goetz, S. J. and Davlasheridze, M. (2017). State-level cooperative extension spending and farmer exits. *Applied Economic Perspectives and Policy*, 39:65–86.

Goetz, S. J. and Debertin, D. L. (2001). Why farmers quit: A county-level analysis. *American Journal of Agricultural Economics*, 83:1010–1023.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110:2586–2624.

Grant, J. H., Arita, S., Emlinger, C., Johansson, R., and Xie, C. (2021). Agricultural exports and retaliatory trade actions: An empirical assessment of the 2018/2019 trade conflict. *Applied Economic Perspectives and Policy*, 43:619–640.

Grant, J. H. and Lambert, D. M. (2008). Do regional trade agreements increase members' agricultural trade? *American Journal of Agricultural Economics*, 90:765–782.

Haile, M. G., Kalkuhl, M., and von Braun, J. (2014). Inter- and intra-seasonal crop acreage response to international food prices and implications of volatility. *Agricultural Economics*, 45:693–710.

Haile, M. G., Kalkuhl, M., and von Braun, J. (2016). Worldwide acreage and yield response to international price change and volatility: A dynamic panel data analysis for wheat, rice, corn, and soybeans. *American Journal of Agricultural Economics*, 98:172–190.

Hakobyan, S. and McLaren, J. (2016). Looking for local labor market effects of NAFTA. *Review of Economics and Statistics*, 98:728–741.

He, X. (2020). US agricultural exports and labor market adjustments. *Agricultural Economics*, 51:609–621.

He, X. (2022). Political and economic determinants of export restrictions in the agricultural and food sector. *Agricultural Economics*, 53:439–453.

Hendricks, N. P., Janzen, J. P., and Smith, A. (2015). Futures prices in supply analysis: Are instrumental variables necessary? *American Journal of Agricultural Economics*, 97:22–39.

Hendricks, N. P., Smith, A., and Sumner, D. A. (2014). Crop supply dynamics and the illusion of partial adjustment. *American Journal of Agricultural Economics*, 96:1469–1491.

Hirsch, C. and Oberhofer, H. (2020). Bilateral trade agreements and price distortions in agricultural markets. *European Review of Agricultural Economics*, 47:1009–1044.

Jean, S. and Bureau, J.-C. (2016). Do regional trade agreements really boost trade? evidence from agricultural products. *Review of World Economics*, 152:477–499.

Kazukauskas, A., Newman, C., Clancy, D., and Sauer, J. (2013). Disinvestment, farm size, and gradual farm exit: The impact of subsidy decoupling in a European context. *American Journal of Agricultural Economics*, 95:1068–1087.

Key, N. and Roberts, M. J. (2006). Government payments and farm business survival. *American Journal of Agricultural Economics*, 88:382–392.

Kim, H. and Moschini, G. (2018). The dynamics of supply: U.S. corn and soybeans in the biofuel era. *Land Economics*, 94:593–613.

Kim, K., Chavas, J.-P., Barham, B., and Foltz, J. (2012). Specialization, diversification, and productivity: A panel data analysis of rice farms in Korea. *Agricultural Economics*, 43:687–700.

Kim, K., Chavas, J.-P., Barham, B., and Foltz, J. (2014). Rice, irrigation and downside risk: a quantile analysis of risk exposure and mitigation on Korean farms. *European Review of Agricultural Economics*, 41:775–815.

Kim, Y., Yu, J., and Pendell, D. L. (2020). Effects of crop insurance on farm disinvestment and exit decisions. *European Review of Agricultural Economics*, 47:324–347.

Kimhi, A. and Bollman, R. (1999). Family farm dynamics in Canada and Israel: The case of farm exits. *Agricultural Economics*, 21:69–79.

Koenker, R. and Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, 15:143–156.

Koo, W. W., Kennedy, P. L., and Skripnitchenko, A. (2006). Regional preferential trade agreements: Trade creation and diversion effects. *Review of Agricultural Economics*, 28:408–415.

Kumbhakar, S. C. (1993). Short-run returns to scale, farm-size, and economic efficiency. *The Review of Economics and Statistics*, 75:336.

Lambert, D. and McKoy, S. (2009). Trade creation and diversion effects of preferential trade associations on agricultural and food trade. *Journal of Agricultural Economics*, 60:17–39.

Li, Y., Miao, R., and Khanna, M. (2019). Effects of ethanol plant proximity and crop prices on land-use change in the United States. *American Journal of Agricultural Economics*, 101:467–491.

Luckstead, J. (2022). Impacts of bilateral trade agreements between the United States and Latin American countries on agri-food trade. *Journal of Agricultural and Resource Economics*, 47:673–696.

Magee, C. S. P. (2008). New measures of trade creation and trade diversion. *Journal of International Economics*, 75:349–362.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71:1695–1725.

Miao, R., Khanna, M., and Huang, H. (2016). Responsiveness of crop yield and acreage to prices and climate. *American Journal of Agricultural Economics*, 98:191–211.

Miljkovic, D. and Paul, R. (2003). Agricultural trade in North America: Trade creation, regionalism and regionalisation. *Australian Journal of Agricultural and Resource Economics*, 47:349–366.

Mills, D. E. and Schumann, L. (1985). Industry structure with fluctuating demand. *The American Economic Review*, 75:758–767.

Ministry of Trade, Industry and Energy (MOTIE) (2024). FTAs in Korea. https://fta.go.kr/main/situation/kfta/lov5/cl.

Nerlove, M. (1956). Estimates of the elasticities of supply of selected agricultural commodities. *Journal of Farm Economics*, 38:496.

Park, S.-H. and Koo, M. G. (2007). Forming a cross-regional partnership: The South Korea-Chile FTA and its implications. *Pacific Affairs*, 80:259–278.

Pates, N. J. and Hendricks, N. P. (2021). Fields from afar: Evidence of heterogeneity in United States corn rotational response from remote sensing data. *American Journal of Agricultural Economics*, 103:1759–1782.

Prina, S. (2013). Who benefited more from the North American Free Trade Agreement: Small or large farmers? evidence from Mexico. *Review of Development Economics*, 17:594–608.

Quiroga, R. E. and Bravo-Ureta, B. E. (1992). Short- and long-run adjustments in dairy production: A profit function analysis. *Applied Economics*, 24:607–616.

Roberts, M. J. and Schlenker, W. (2013). Identifying supply and demand elasticities of agricultural commodities: Implications for the US ethanol mandate. *American Economic Review*, 103:2265–2295.

Santeramo, F. G., Goodwin, B. K., Adinolfi, F., and Capitanio, F. (2016). Farmer participation, entry and exit decisions in the Italian crop insurance programme. *Journal of Agricultural Economics*, 67:639–657.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106:15594–15598.

Statistics Korea (2021). KOrean Statistical Information Service. https://kosis.kr/eng.

Storm, H., Mittenzwei, K., and Heckelei, T. (2015). Direct payments, spatial competition, and farm survival in Norway. *American Journal of Agricultural Economics*, 97:1192–1205.

Sun, L. and Reed, M. R. (2010). Impacts of free trade agreements on agricultural trade creation and trade diversion. *American Journal of Agricultural Economics*, 92:1351–1363.

Susanto, D., Rosson, C. P., and Adcock, F. J. (2007). Trade creation and trade diversion in the North American Free Trade Agreement: The case of the agricultural sector. *Journal of Agricultural and Applied Economics*, 39:121–134.

USDA ERS (2024). Feed grains yearbook data tables - all years. *Feed Grains Database.* https://www.ers.usda.gov/data-products/feed-grains-database.

USDA FAS (2024). Product groups - BICO HS-6. *Global Agricultural Trade System.* https://apps.fas.usda.gov/gats/default.aspx.

USDA NASS (2024). Quick stats. https://quickstats.nass.usda.gov.

World Bank (2024). World Integrated Trade Solution. https://wits.worldbank.org.

WTO (2024). RTAs in force. *Regional Trade Agreements Database.* https://rtais.wto.org/UI/PublicAllRTAList.aspx.

Yu, J., Smith, A., and Sumner, D. A. (2018). Effects of crop insurance premium subsidies on crop acreage. *American Journal of Agricultural Economics*, 100:91–114.

Yu, J., Villoria, N. B., and Hendricks, N. P. (2022). The incidence of foreign market tariffs on farmland rental rates. *Food Policy*, 112:102343.

# Appendix A

# Appendix to Chapter 2

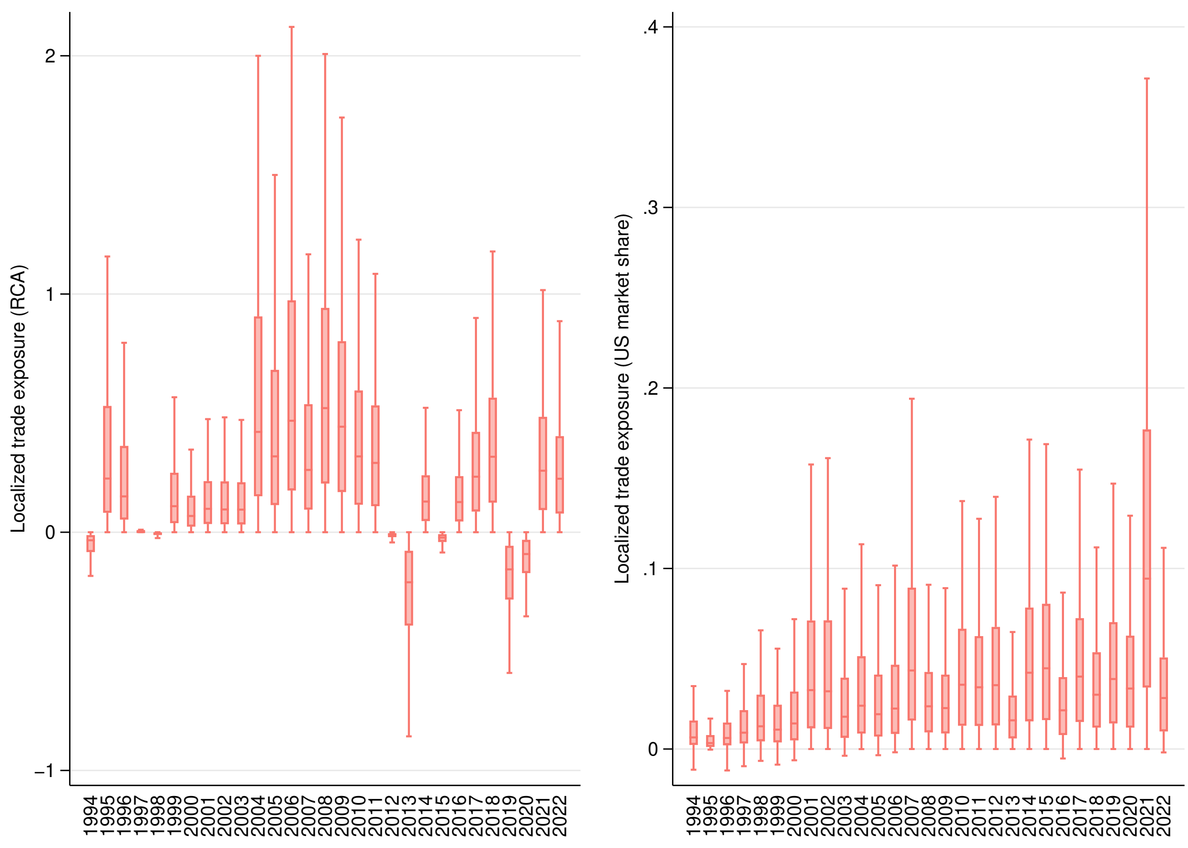


Figure A.1: Boxplots of localized trade exposure for corn (1994-2022)

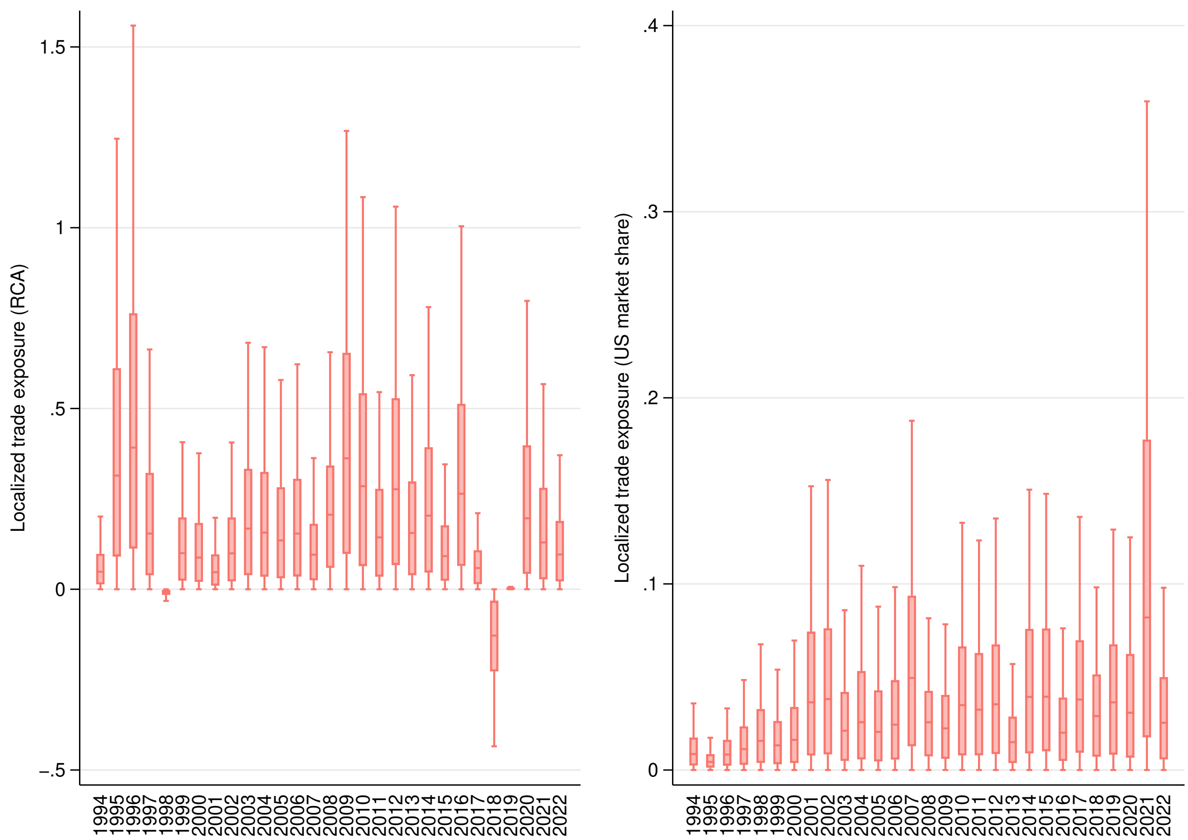


Figure A.2: Boxplots of localized trade exposure for soybeans (1994-2022)

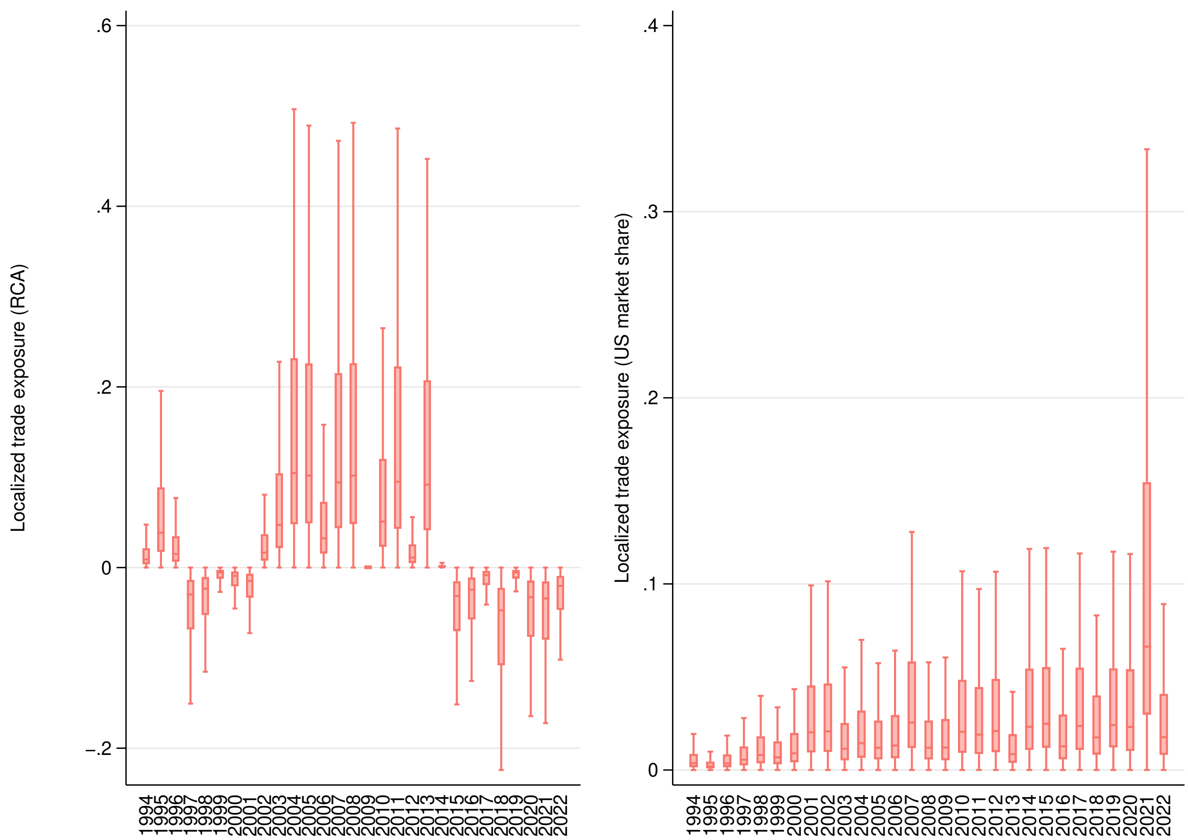


Figure A.3: Boxplots of localized trade exposure for wheat (1994-2022)

# Appendix B

# Appendix to Chapter 3

Table B.1: Descriptive statistics of farm-level observations by year (all variables)

| | (1) Overall | (2) 1991-1993 | (3) 2020-2022 |
|---|---|---|---|
| Net farm income ($thousand) | 62.72 | 27.20 | 268.92 |
| | (135.95) | (34.17) | (366.75) |
| Share of Corn (%) | 15.41 | 10.30 | 23.51 |
| | (18.06) | (15.16) | (18.49) |
| Share of Soybeans (%) | 24.32 | 17.24 | 42.19 |
| | (24.34) | (21.45) | (23.56) |
| Share of Wheat (%) | 33.73 | 37.92 | 22.18 |
| | (23.69) | (21.58) | (21.19) |
| Trade exposure (RCA base) | 2.22 | 1.98 | 2.08 |
| | (1.16) | (0.95) | (1.15) |
| Trade exposure (U.S. market share base) | 0.19 | 0.12 | 0.32 |
| | (0.14) | (0.11) | (0.17) |

| | (1) Overall | (2) 1991-1993 | (3) 2020-2022 |
|---|---|---|---|
| Total farm capital ($million) | 2.11 | 0.66 | 8.21 |
| | (3.22) | (0.45) | (7.03) |
| Value of farm production ($thousand) | 286.41 | 110.95 | 989.96 |
| | (418.94) | (91.27) | (1,007.32) |
| Machinery and equipment value ($thousand) | 204.04 | 56.85 | 732.34 |
| | (310.63) | (46.91) | (730.08) |
| Farm type | 1.92 | 1.54 | 5.57 |
| | (6.24) | (3.65) | (14.84) |
| Number of operators | 0.98 | 1.02 | 0.94 |
| | (0.38) | (0.35) | (0.46) |
| Number of workers | 1.37 | 1.40 | 1.45 |
| | (0.93) | (0.99) | (1.16) |
| Number of family dependents | 2.62 | 2.92 | 2.11 |
| | (1.34) | (1.50) | (0.90) |
| Crop-labor fraction | 0.95 | 0.95 | 0.95 |
| | (0.08) | (0.08) | (0.07) |
| Observations | 14,090 | 2,067 | 490 |

# Appendix C

# Appendix to Chapter 4

## Weighted import exposure

In the main analysis, the import exposure is based on the individual farms' initial crop shares that are computed by unweighted revenue. We examine whether the results are robust to the way we compute the import exposure. Tables C.1–C.3 report the estimation results using the import exposure from Chile, which are based on the weighted crop revenue for individual farms.

Table C.1: The effects of import exposure from Chile on farm economy: Weighted import exposure

| VARIABLES | (1) Crop Revenue (2003 million KRW) | (2) | (3) Farm Profit (2003 million KRW) | (4) | (5) Labor Cost (2003 million KRW) | (6) |
|---|---|---|---|---|---|---|
| F & V Import – Chile | -0.0209 | -0.0422** | -0.0343** | -0.0521** | 0.0031 | 0.0033 |
| (2003 million KRW) | (0.0192) | (0.0181) | (0.0170) | (0.0207) | (0.0046) | (0.0047) |
| Observations | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.2: UQR estimates of the effects of import exposure from Chile on farm economy: Weighted import exposure

| VARIABLES | (1) $\tau = .25$ | (2) $\tau = .50$ | (3) $\tau = .75$ |
|---|---|---|---|
| *Dependent variable: Crop revenue* | | | |
| F & V Import – Chile | 0.0103*** | 0.0008 | -0.0718*** |
| | (0.0038) | (0.0060) | (0.0260) |
| *Dependent variable: Farm profit* | | | |
| F & V Import – Chile | -0.0040 | -0.0175 | -0.1113*** |
| | (0.0075) | (0.0109) | (0.0204) |
| *Dependent variable: Labor cost* | | | |
| F & V Import – Chile | 0.0001 | 0.0000 | -0.0026 |
| | (0.0001) | (0.0001) | (0.0016) |
| Observations | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes |

Note: All regressions include a constant and the control variables. Both dependent and key independent variables are in 2003 million KRW. Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

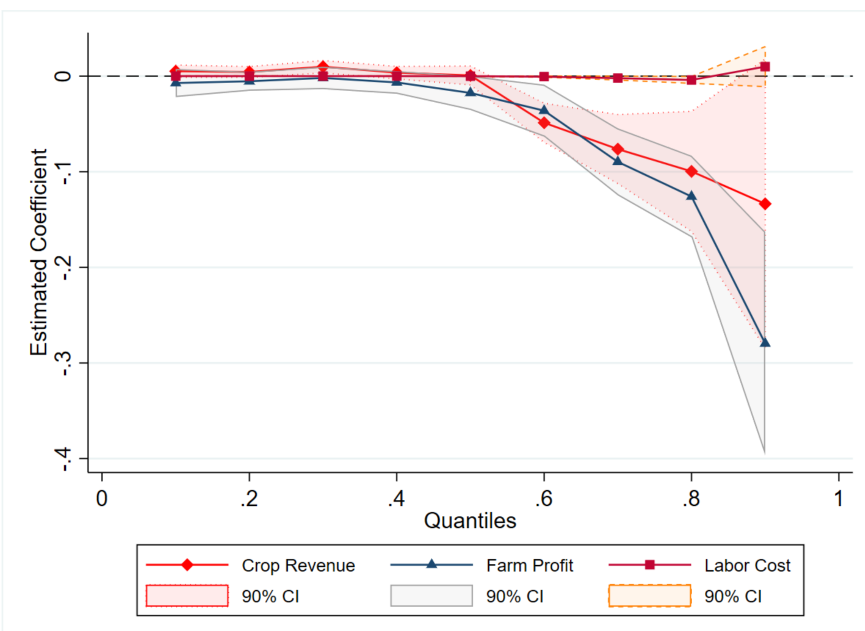


Figure C.1: UQR estimates of the effect of imports from Chile: Weighted import exposure

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

Table C.3: The effects of import exposure from Chile on the share of fruits and vegetables: Weighted import exposure

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | $(Share\ of\ Fruits\ \&\ Vegetables) \times 100$ | | | | |
| | OLS | | UGR | | |
| VARIABLES | | | $\tau = .25$ | $\tau = .50$ | $\tau = .75$ |
| F & V Import – Chile | -0.0320*** | -0.0282** | -0.0275*** | -0.0554* | -0.0460* |
| (2003 million KRW) | (0.0111) | (0.0117) | (0.0093) | (0.0317) | (0.0273) |
| Observations | 4,837 | 4,837 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | Yes | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

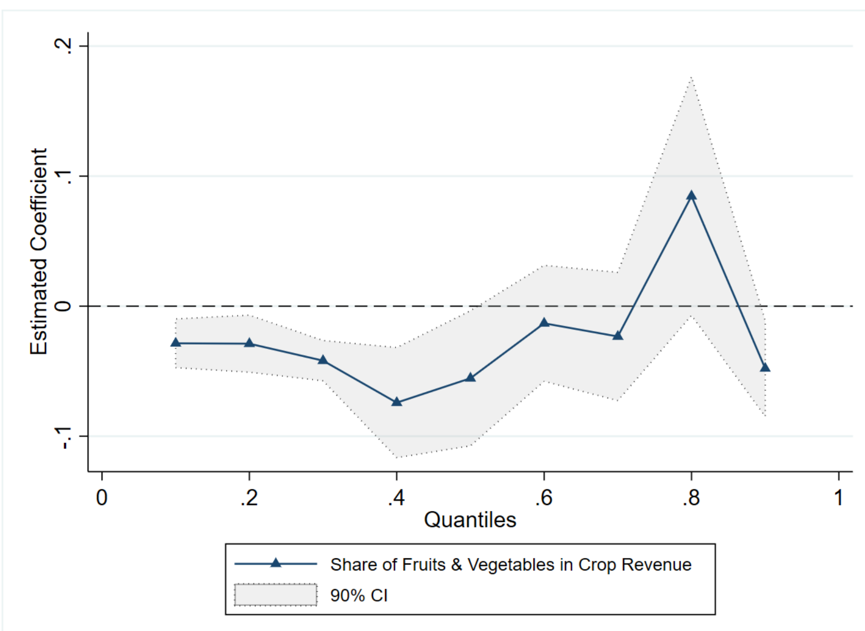


Figure C.2: UQR estimates of the effect of imports from Chile on the share of fruits and vegetables: Weighted import exposure

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

## Expansion of sample period: 2003 to 2007

To check the robustness of our results, we test whether the results are sensitive to the periods of data. We estimate the effects of import exposure using full samples from 2003 to 2007. In this sample, we keep the same sample restrictions used in the main analysis (e.g. farms identified in 2003 and farms with non-negative value of farm receipts).

Table C.4: The effects of import exposure from Chile on farm economy: Years in 2003–2007

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Crop Revenue (2003 million KRW) | | Farm Profit (2003 million KRW) | | Labor Cost (2003 million KRW) | |
| F & V Import – Chile | -0.1261** | -0.1492*** | -0.0894*** | -0.1202*** | -0.0118 | -0.0130 |
| (2003 million KRW) | (0.0592) | (0.0476) | (0.0300) | (0.0272) | (0.0130) | (0.0126) |
| Observations | 6,478 | 6,478 | 6,478 | 6,478 | 6,478 | 6,478 |
| Farm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

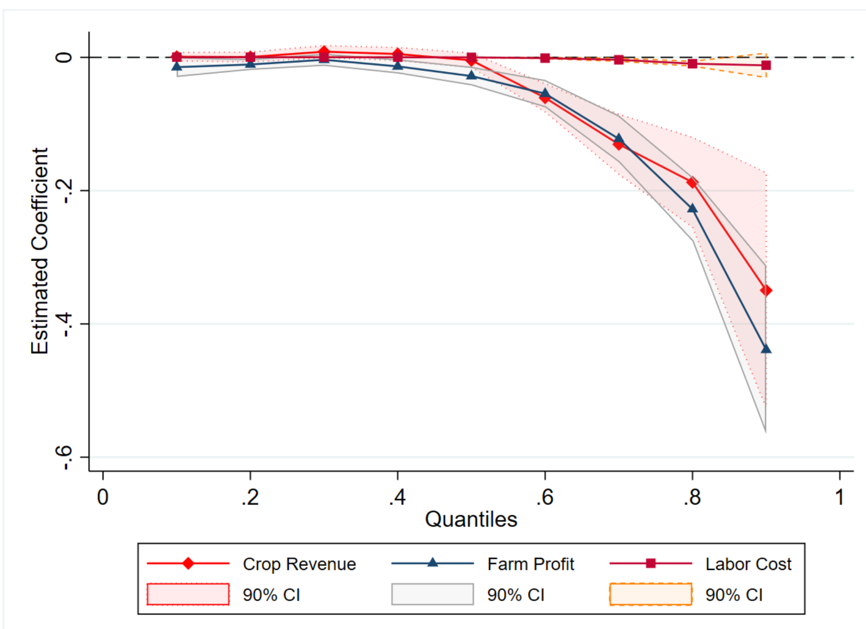


Figure C.3: UQR estimates of the effect of imports from Chile: Years in 2003–2007

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

Table C.5: UQR estimates of the effects of import exposure from Chile on farm economy: Years in 2003–2007

| VARIABLES | (1) $\tau = .25$ | (2) $\tau = .50$ | (3) $\tau = .75$ |
|---|---|---|---|
| *Dependent variable: Crop revenue* | | | |
| F & V Import – Chile | 0.0056 | -0.0045 | -0.1495*** |
| | (0.0056) | (0.0066) | (0.0320) |
| *Dependent variable: Farm profit* | | | |
| F & V Import – Chile | -0.0079 | -0.0281*** | -0.1600*** |
| | (0.0053) | (0.0086) | (0.0250) |
| *Dependent variable: Labor cost* | | | |
| F & V Import – Chile | 0.0002 | -0.0001 | -0.0074*** |
| | (0.0002) | (0.0002) | (0.0021) |
| Observations | 6,478 | 6,478 | 6,478 |
| Farm FE | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes |

Note: All regressions include a constant and the control variables. Both dependent and key independent variables are in 2003 million KRW. Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.6: The effects of import exposure from Chile on the share of fruits and vegetables: Years in 2003–2007

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | $(Share\ of\ Fruits\ \&\ Vegetables) \times 100$ | | | | |
| | OLS | | UGR | | |
| VARIABLES | | | $\tau = .25$ | $\tau = .50$ | $\tau = .75$ |
| F & V Import – Chile | 0.0612*** | -0.0503*** | -0.0618*** | -0.0939*** | -0.0829** |
| (2003 million KRW) | (0.0144) | (0.0141) | (0.0112) | (0.0283) | (0.0381) |
| Observations | 6,447 | 6,447 | 6,478 | 6,478 | 6,478 |
| Farm FE | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | Yes | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

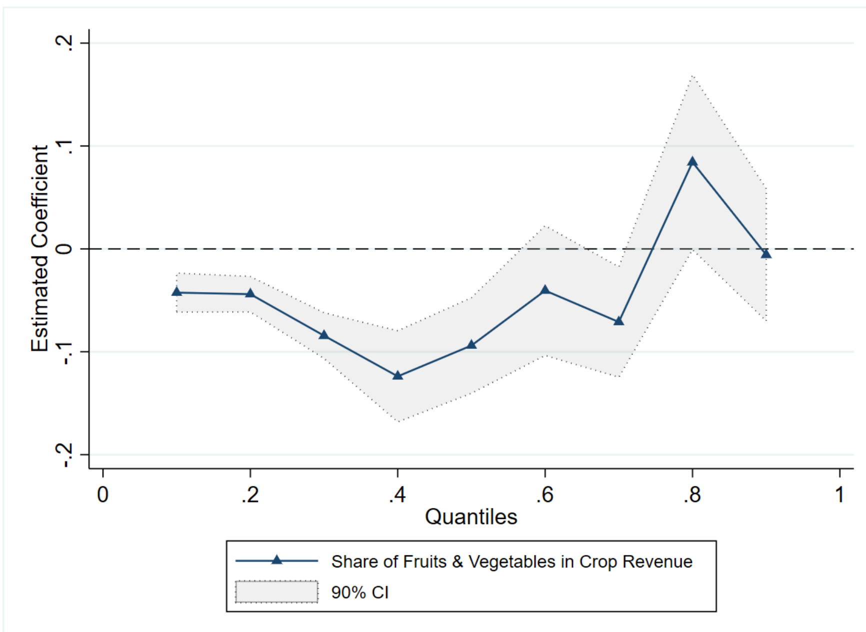


Figure C.4: UQR estimates of the effect of imports from Chile on the share of fruits and vegetables: Years in 2003–2007

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

## Inclusion of negative inventory values

We are concerned that the effects derived from the inventory reduction can be included, if we use sample with any negative value of farm receipts. Tables C.7–C.9 present the estimation results using sample that includes farms that have negative farm receipts.

Table C.7: The effects of import exposure from Chile on farm economy: Inclusion of negative inventory values

| VARIABLES | (1) Crop Revenue (2003 million KRW) | (2) | (3) Farm Profit (2003 million KRW) | (4) | (5) Labor Cost (2003 million KRW) | (6) |
|---|---|---|---|---|---|---|
| F & V Import – Chile | -0.0763 | -0.0903 | -0.0701 | -0.0887* | -0.0049 | -0.0045 |
| (2003 million KRW) | (0.0669) | (0.0608) | (0.0449) | (0.0446) | (0.0099) | (0.0091) |
| Observations | 8,003 | 8,003 | 8,003 | 8,003 | 8,003 | 8,003 |
| Farm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.8: UQR estimates of the effects of import exposure from Chile on farm economy: Inclusion of negative inventory values

| VARIABLES | (1) $\tau = .25$ | (2) $\tau = .50$ | (3) $\tau = .75$ |
|---|---|---|---|
| *Dependent variable: Crop revenue* | | | |
| F & V Import – Chile | 0.0138*** | 0.0065 | -0.0847*** |
| | (0.0043) | (0.0059) | (0.0262) |
| *Dependent variable: Farm profit* | | | |
| F & V Import – Chile | -0.0019 | -0.0172** | -0.1148*** |
| | (0.0048) | (0.0066) | (0.0215) |
| *Dependent variable: Labor cost* | | | |
| F & V Import – Chile | 0.0002 | -0.0001 | -0.0060*** |
| | (0.0001) | (0.0001) | (0.0011) |
| Observations | 8,003 | 8,003 | 8,003 |
| Farm FE | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes |

Note: All regressions include a constant and the control variables. Both dependent and key independent variables are in 2003 million KRW. Cluster-robust standard errors are clustered by province and year and reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1

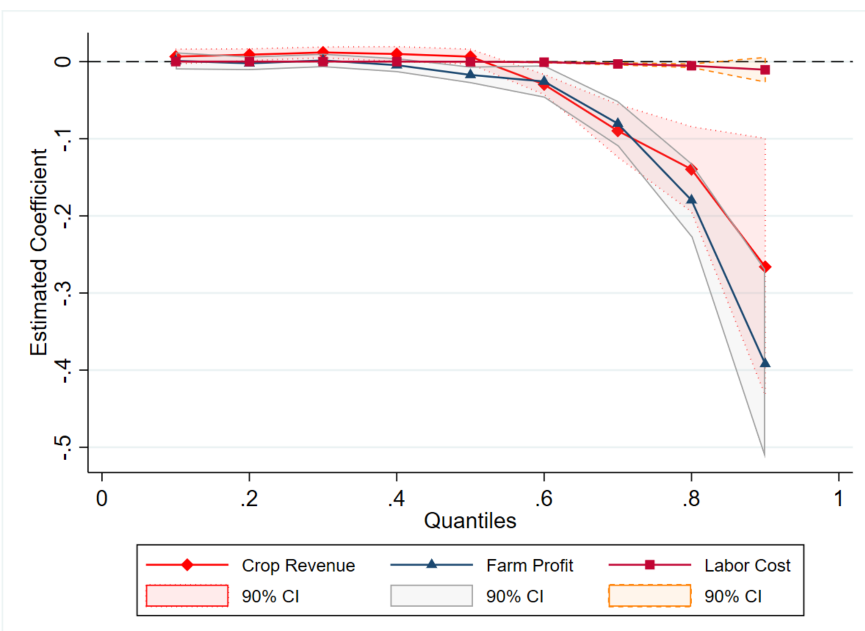


Figure C.5: UQR estimates of the effect of imports from Chile: Inclusion of negative inventory values

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

Table C.9: The effects of import exposure from Chile on the share of fruits and vegetables: Inclusion of negative inventory values

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | $(Share\ of\ Fruits\ \&\ Vegetables) \times 100$ | | | | |
| | OLS | | UGR | | |
| VARIABLES | | | $\tau = .25$ | $\tau = .50$ | $\tau = .75$ |
| F & V Import – Chile | -0.0135 | -0.0095 | -0.0645*** | -0.0890*** | -0.0476 |
| (2003 million KRW) | (0.0273) | (0.0324) | (0.0103) | (0.0246) | (0.0329) |
| Observations | 7,977 | 7,977 | 8,003 | 8,003 | 8,003 |
| Farm FE | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | Yes | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

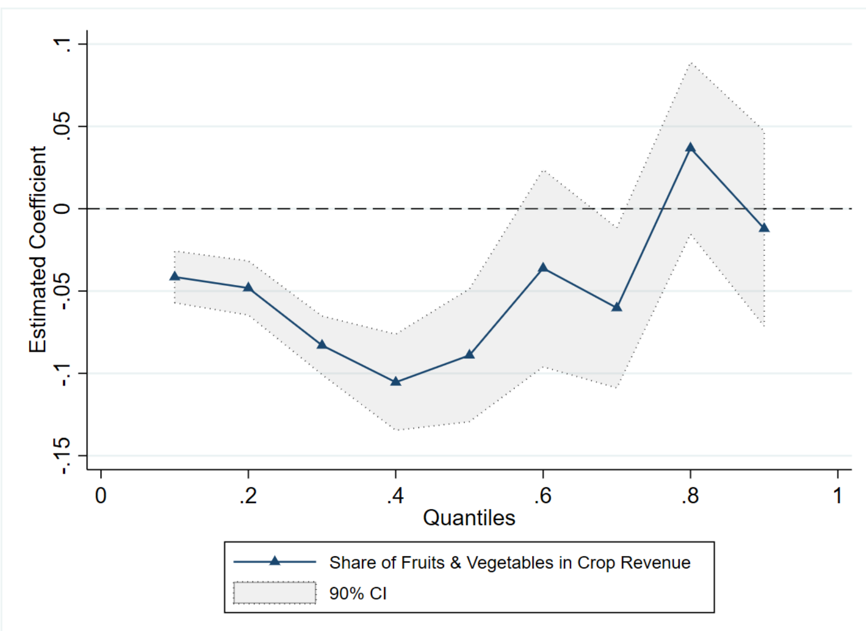


Figure C.6: UQR estimates of the effect of imports from Chile on the share of fruits and vegetables: Inclusion of negative inventory values

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

## IHS transformation

To see whether our results are sensitive to an alternate functional form, we use the inverse hyperbolic sine (IHS) transformation, which can handle negative values whereas the logarithm transformation cannot. Tables C.10 and C.11 report the results of OLS estimation and UQR using the dependent variables which are IHS transformed.

Table C.10: The effects of import exposure from Chile on farm economy: IHS transformation

| VARIABLES | (1) IHS(Crop Revenue) | (2) | (3) IHS(Farm Profit) | (4) | (5) IHS(Labor Cost) | (6) |
|---|---|---|---|---|---|---|
| F & V Import – Chile | 0.0004 | -0.0010* | -0.0016 | -0.0050* | -0.0001 | -0.0002 |
| (2003 million KRW) | (0.0005) | (0.0005) | (0.0021) | (0.0027) | (0.0007) | (0.0007) |
| Observations | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

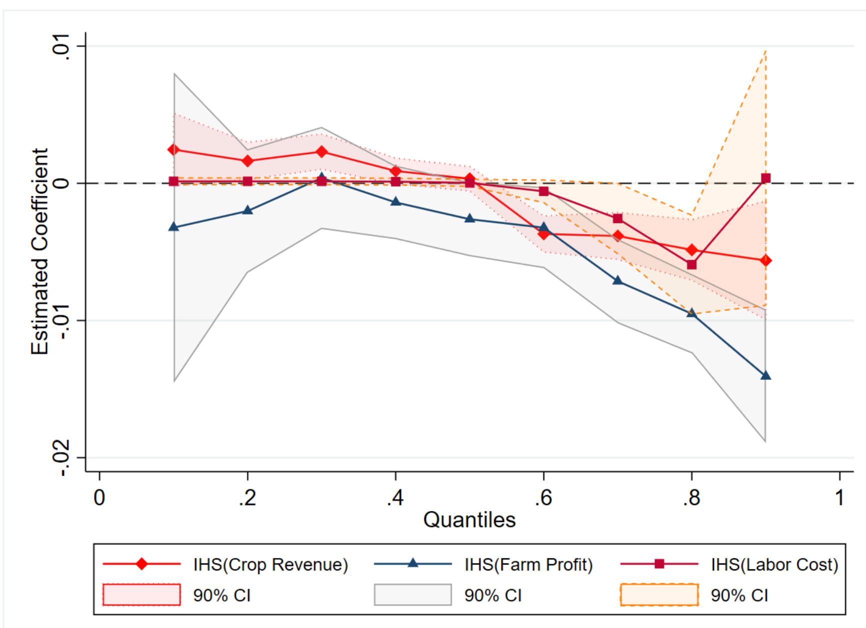


Figure C.7: UQR estimates of the effect of imports from Chile: IHS transformation

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

Table C.11: UQR estimates of the effects of import exposure from Chile on farm economy: IHS transformation

| VARIABLES | (1)<br>$\tau = .25$ | (2)<br>$\tau = .50$ | (3)<br>$\tau = .75$ |
|---|---|---|---|
| *Dependent variable: IHS(Crop revenue)* | | | |
| F & V Import – Chile | 0.0025*** | 0.0003 | -0.0037*** |
| (2003 million KRW) | (0.0009) | (0.0005) | (0.0012) |
| *Dependent variable: IHS(Farm profit)* | | | |
| F & V Import – Chile | -0.0008 | -0.0026 | -0.0082*** |
| (2003 million KRW) | (0.0026) | (0.0016) | (0.0019) |
| *Dependent variable: IHS(Labor cost)* | | | |
| F & V Import – Chile | 0.0001 | 0.0000 | -0.0040** |
| (2003 million KRW) | (0.0002) | (0.0002) | (0.0019) |
| Observations | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes |

Note: All regressions include a constant and the control variables. Both dependent and key independent variables are in 2003 million KRW. Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

## Jackknife standard error

Tables C.12–C.14 report the estimation results with the jackknife standard errors.

Table C.12: The effects of import exposure from Chile on farm Economy: Jackknife standard error

| VARIABLES | (1) Crop Revenue (2003 million KRW) | (2) | (3) Farm Profit (2003 million KRW) | (4) | (5) Labor Cost (2003 million KRW) | (6) |
|---|---|---|---|---|---|---|
| F & V Import – Chile | -0.0285 | -0.0562* | -0.0351* | -0.0593* | 0.0056 | 0.0057 |
| (2003 million KRW) | (0.0291) | (0.0305) | (0.0307) | (0.0345) | (0.0060) | (0.0063) |
| Observations | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C.13: UQR estimates of the effects of import exposure from Chile on farm economy: Jackknife standard error

| VARIABLES | (1)<br>$\tau = .25$ | (2)<br>$\tau = .50$ | (3)<br>$\tau = .75$ |
|---|---|---|---|
| *Dependent variable: Crop revenue* | | | |
| F & V Import – Chile | 0.0140** | 0.0039 | -0.0965*** |
| | (0.0058) | (0.0095) | (0.0284) |
| *Dependent variable: Farm profit* | | | |
| F & V Import – Chile | -0.0025 | -0.0176 | -0.1204*** |
| | (0.0095) | (0.0142) | (0.0360) |
| *Dependent variable: Labor cost* | | | |
| F & V Import – Chile | 0.000149 | 0.000032 | -0.004468* |
| | (0.000138) | (0.000151) | (0.002365) |
| Observations | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes |

Note: All regressions include a constant and the control variables. Both dependent and key independent variables are in 2003 million KRW. Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.14: The effects of import exposure from Chile on the share of fruits and vegetables: Jackknife standard error

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | $(Share\ of\ Fruits\ \&\ Vegetables) \times 100$ | | | | |
| | OLS | | UGR | | |
| VARIABLES | | | $\tau = .25$ | $\tau = .50$ | $\tau = .75$ |
| F & V Import – Chile | -0.0384** | -0.0335** | -0.0420** | -0.0665** | -0.0474 |
| (2003 million KRW) | (0.0152) | (0.0147) | (0.0197) | (0.0327) | (0.0440) |
| Observations | 4,837 | 4,837 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | Yes | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1

## Fruits and vegetable import Exposure from the world

We also use the import exposure from the world as the variable of interest.[1]

Table C.15: The List of 6-digit HS codes used in import data

| HS code | Commodity | List |
|---|---|---|
| 07 | Edible vegetables and certain roots and tubers | 070200, 070310, 070320, 070390, 070410, 070420, 070490, 070511, 070519, 070521, 070529, 070610, 070690, 070700, 070910, 070920, 070930, 070940, 070960, 070970, 070990, 071030, 071040, 071080, 071090, 071120, 071130, 071140, 071190, 071220, 071290 |
| 08 | Edible fruit and nuts; peel of citrus fruit or melons | 080111, 080121, 080122, 080131, 080132, 080211, 080212, 080221, 080222, 080231, 080232, 080240, 080250, 080290, 080300, 080410, 080420, 080430, 080440, 080450, 080510, 080520, 080540, 080550, 080590, 080610, 080711, 080719, 080720, 080820, 080910, 080920, 080940, 081030, 081050, 081060, 081090, 081110, 081190, 081290, 081340 |
| 09 | Coffee, tea, and spices | 090411, 090412, 090420, 091010 |
| 12 | Oil seeds and oleaginous fruits | 121190 |
| 20 | Preparations of vegetables, fruit or nuts | 200590, 200819 |

Source: UN Comtrade

Tables C.16–C.18 report the results when we replace import exposure from Chile with that from the world.

[1] A total of 79 HS 2002 codes is used to construct the import value from the world. More detailed list of 6-digit HS 2002 codes is in table C.15.

Table C.16: The effects of import exposure from the world on farm economy

| VARIABLES | (1) Crop Revenue (2003 million KRW) | (2) | (3) Farm Profit (2003 million KRW) | (4) | (5) Labor Cost (2003 million KRW) | (6) |
|---|---|---|---|---|---|---|
| F & V Import – World | -0.0028 | -0.0054 | -0.0030 | -0.0053 | 0.0006 | 0.0006 |
| | (0.0036) | (0.0039) | (0.0039) | (0.0044) | (0.0009) | (0.0009) |
| Observations | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses.

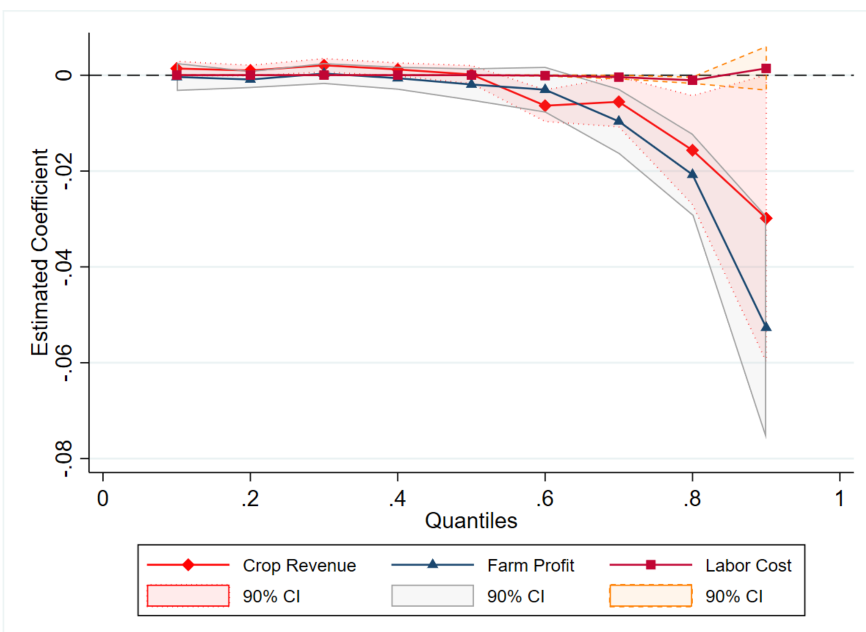


Figure C.8: UQR estimates of the effect of imports from the world on farm economy
Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

Table C.17: UQR estimates of the effects of import exposure from the world on farm economy

| VARIABLES | (1) $\tau = .25$ | (2) $\tau = .50$ | (3) $\tau = .75$ |
|---|---|---|---|
| *Dependent variable: Crop revenue* | | | |
| F & V Import – World | 0.0017** | 0.0002 | -0.0097** |
| | (0.0008) | (0.0012) | (0.0046) |
| *Dependent variable: Farm profit* | | | |
| F & V Import – World | -0.0006 | -0.0019 | -0.0130** |
| | (0.0013) | (0.0021) | (0.0050) |
| *Dependent variable: Labor cost* | | | |
| F & V Import – World | 0.0000 | 0.0000 | -0.0006* |
| | (0.0000) | (0.0000) | (0.0003) |
| Observations | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes |

Note: All regressions include a constant and the control variables. Both dependent and key independent variables are in 2003 million KRW. Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.18: The effects of import exposure from the world on the share of fruits and vegetables

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | $(Share\ of\ Fruits\ \&\ Vegetables) \times 100$ | | | | |
| | OLS | | UGR | | |
| VARIABLES | | | $\tau = .25$ | $\tau = .50$ | $\tau = .75$ |
| F & V Import – World | -0.0040* | -0.0030 | -0.0051** | -0.0075 | -0.0067 |
| | (0.0023) | (0.0019) | (0.0024) | (0.0054) | (0.0053) |
| Observations | 4,837 | 4,837 | 4,864 | 4,864 | 4,864 |
| Farm FE | Yes | Yes | Yes | Yes | Yes |
| Province-by-Year FE | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | Yes | Yes |

Note: Cluster-robust standard errors are clustered by province and year and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

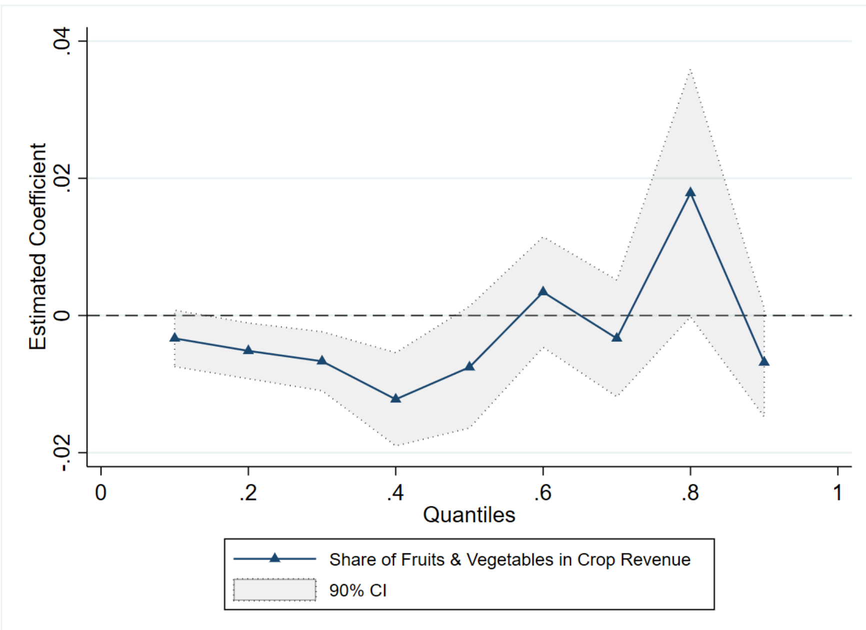


Figure C.9: UQR estimates of the effect of imports from the world on the share of fruits and vegetable

Note: 90% confidence intervals of the coefficients are calculated by cluster-robust standard errors.

## Difference-in-differences approach

We utilize a difference-in-differences (DiD) approach to identify the causal effects of the Korea-Chile FTA on fruits and vegetable farms. The treated group is farms that produce fruits and vegetable and the control group is farms that mainly produce other agricultural commodities, including rice, wheat, mixed grain, pulses, potatoes, floriculture crops, specialty crops, and agricultural byproducts. We estimate the impact of the Korea-Chile FTA on fruits and vegetable farm economy, based on the full samples from 2003 to 2007 and the following equation:

$$y_{it} = \gamma F\&V_i + \lambda FTA_t + \delta(F\&V_i \times FTA_t) + X_{it}'\Gamma + \epsilon_{it}$$

where $y_{it}$ indicates the dependent variables, which are the crop revenue, farm profit, labor cost, and the share of fruits and vegetable, for farm $i$ in year $t$, $F\&V_i$ and $FTA_t$ are the indicators of fruits and vegetable farms and post Korea-Chile FTA, $X_{it}'$ is a vector of covariates, and $\epsilon_{it}$ is the error term. Table C.19 reports the results of the DiD estimation. The results show that the Korea-Chile FTA had a negative influence on all farm outcomes except for the labor cost.

Table C.19: The effects of the Korea-Chile FTA on fruits and vegetable farms

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Crop Revenue | | Farm Profit | | Labor Cost | | Share of F & V | |
| VARIABLES | (2003 million KRW) | | (2003 million KRW) | | (2003 million KRW) | | (%) | |
| $F\&V \times FTA$ | -0.12 | -3.12*** | 0.21 | -2.53*** | -0.05 | -0.24 | -0.02* | -0.05*** |
| | (1.29) | (1.03) | (0.95) | (0.85) | (0.19) | (0.18) | (0.01) | (0.01) |
| Observations | 6,757 | 6,757 | 6,757 | 6,757 | 6,757 | 6,757 | 6,725 | 6,725 |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |

Note: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## Heterogeneous effects of import exposure

To examine how the impact of import exposure varies by farm characteristics, we interact the import exposure with farm characteristics, $x_{it}$, such as non-farm income, agricultural subsidy, farming types, farm acreage size, indicators of full-time farm, business types, the age of farm owner, the number of household members, and the educational attainment of farm owner. We estimate the following regression equation using OLS:

$$y_{it} = \beta_0 + \beta_1 Import_{it} + X_{it}'\Gamma + \beta_2(Import_{it} \times x_{it}) + u_i + v_{st} + \epsilon_{it}$$

where the parameter $\beta_2$ is the correlation of farm outcome with a farm characteristic of interest interacted with import exposure. Figure C.10 presents the heterogeneous effects of import exposure on crop revenue by characteristics of interest. The effect of import exposure from Chile on crop revenue differs by non-farm income, but it does not show a statistically significant difference in agricultural subsidy. By farming types, the impact of import exposure from Chile is statistically heterogeneous for fruits and vegetable farms compared to rice farms. For the differential effects of import exposure based on farm size, the findings suggest that some mid-size farms experienced greater impacts compared to smaller farms. Although these results are not statistically significant, they align with the findings of quantile estimations as these mid-size farms are generally focusing on high-value crops. In addition, we find that the overall interactions between import exposure and characteristics of interest are statistically significant except for educational attainment, implying that farm characteristics play roles differently in the effect of Chilean import exposure on crop revenue.

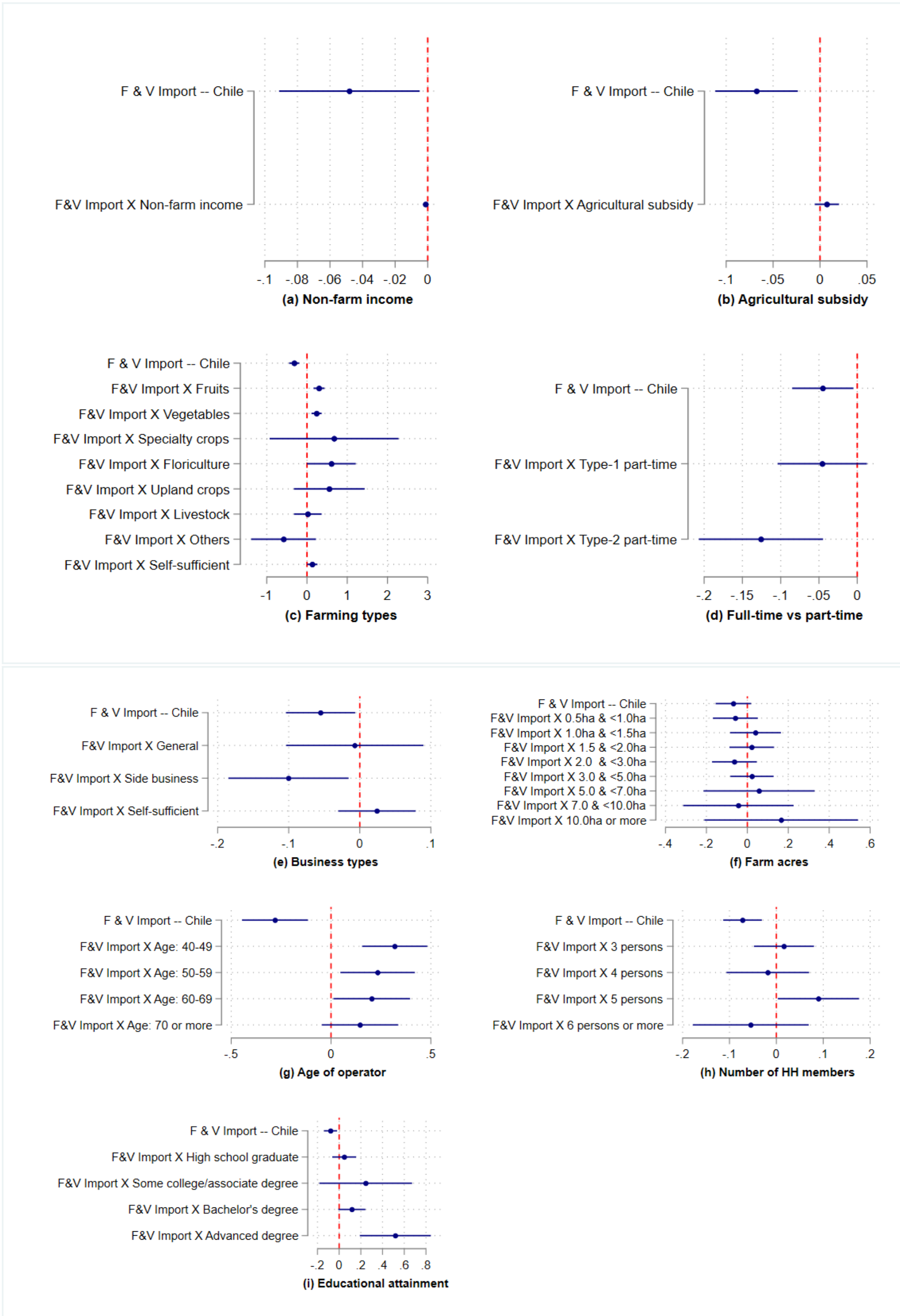


Figure C.10: Heterogeneous effects of import exposure on crop revenue by farm characteristics

Note: The baselines for the categorical variables are as follows: farming types (rice), full-time vs part-time (full-time), business types (specialized), farm acres (less than 0.5 ha), age of owner (less than 40), number of household members (2 persons), educational attainment (less than high school). The spikes indicate 95% confidence intervals of the coefficients.