The Incidence of Foreign Market Accessibility on Farmland Rental Rates

Jisang Yu* Nelson B. Villoria† Nathan P. Hendricks‡

April 20, 2020

Abstract

Agriculture in the U.S. relies critically on exports and it is important to quantify the incidence of foreign market accessibility on factor prices to understand economic consequences of agricultural trade policies. In this paper, we estimate how farmland rental rates are affected by the tariffs that U.S. export crops face. Using annual county-level data of cash rents for non-irrigated fields in 2,534 U.S. counties, we first directly estimate the impact of the tariffs that U.S. export crops face on cash rents. Constructing a localized measure of the tariff exposure to the U.S. exports and the estimation of the impact of the localized measure on the cash rents face two aggregation problems that lead to identification challenges: a) aggregating export tariffs across trading partners to obtain crop-specific tariffs that the U.S. exports face, and b) aggregating the crop-specific export tariffs across crops to obtain the localized measure. We tackle these challenges by modifying and extending the shift-share design literature. Our finding indicates that one percent increase in ad valorem equivalent of the localized tariff reduces the cash rents by about 2.6–5.3% point. In order to place the estimated coefficients in the context of the recent trade war between the U.S. and China, we also provide the predicted changes in the cash rents caused by the 2018 Chinese retaliatory tariffs. Our results indicate that the 2018 Chinese retaliatory tariffs would reduce the cash rents by about 2%.

*Assistant Professor, Department of Agricultural Economics, Kansas State University, jisangyu@ksu.edu
†Associate Professor, Department of Agricultural Economics, Kansas State University, nvilloria@ksu.edu
‡Associate Professor, Department of Agricultural Economics, Kansas State University, nph@ksu.edu

1 Introduction

The importance of international markets for U.S. agriculture is difficult to overstate. As U.S. agricultural production grows faster than domestic demand, the importance of export markets becomes larger; for instance, about 20% of grains, and 39% of oilseeds are sold overseas (USDA, 2019b). The reliance of U.S. agriculture on export markets has been greatly facilitated by efforts to lower trade barriers. For example, the implementation of the North American Free Trade Agreement (NAFTA) in 1994 contributed to a 68 % increase in U.S. agricultural exports to Canada and Mexico within five years of its signature (Jiang, 2016). Similarly, U.S. agricultural exports to China increased nearly 185% within the five years following China's accession to the World Trade Organization (WTO) in 2001 (FAS, 2018). While U.S. agricultural imports have also grown substantially, the agricultural sector has displayed steady trade surpluses (Beckman, Dyck, and Heerman, 2017). Moreover, about a third of farm cash receipts come from agricultural exports (Schnepf, 2017). The benefits of agricultural exports spill over to the wider economy: it is estimated that, as recently as 2016, agriculture exports sustained more than one million full-time jobs, two thirds of which were non-farm (USDA, 2019a).

Although the potential benefits of trade are many, international trade reallocates resources within the economy, resulting in winning and losing sectors. The concerns about these disparate effects are evident in the historical evolution of the studies looking at the effects of increased trade liberalization on wage inequality in the U.S. manufacturing sector. Several studies stated that the impacts of competition with low-income countries on U.S. labor markets had been limited given that low-wage countries had only little influence on U.S. import markets (e.g. Katz and Autor, 1999; Krugman, 2000). However, recent empirical studies on the effects of rapid growth of low-wage countries, particularly China, on regional U.S. labor markets, find lower wages and higher unemployment in the communities most exposed to Chinese imports (Autor, Dorn, and Hanson, 2013; Acemoglu et al., 2015). In contrast to the case of manufacturing, we lack rigorous empirical evidence on the impacts of agricultural trade liberalization on the income of the factors directly employed in U.S. agriculture despite the increasing U.S agricultural exports caused by the recent economic growth in China and other low-income and emerging countries such as Mexico (USDA, 2019a).

Therefore, in this paper, we directly estimate the effect of localized exposure to foreign market accessibility on the farmland rental rates. Our objective is to empirically document the overall effect of the localized exposure to the changes in tariffs that the U.S. exports of agricultural commodities face. Constructing a localized measure of the exposure to the tariffs faced by the U.S. exports and the estimation of the impact of the localized tariff exposure on the U.S. cash rents have two aggregation problems that may lead to identification challenges. First, we need to aggregate the tariffs imposed by various trading partners on the U.S. exports in order to obtain crop-specific tariffs that the U.S. exports face. And then, we compute the localized measure of the tariff exposures by aggregating the crop-specific tariffs across crops at the local level. We discuss how using contemporaneous shares for both aggregation problems leads to endogeneity bias and propose to use the shares of the base period for the aggregations.

We then conduct prediction exercises for the 2018 Chinese retaliatory tariffs using the estimated impact of the changes in the localized tariff exposure with and without considering the trade volume allocations as responses to the retaliatory tariffs. To incorporate the trade volume reallocation, we estimate the counterfactual localized tariffs using the Global Trade Analysis Project (GTAP) model (Hertel, 1997). We focus on the imposition of tariffs on U.S. field crops imposed by China as retaliation from the implementation of U.S. tariffs on Chinese imports (Taheripour and Tyner, 2018; Regmi, 2019). Although the tariffs imposed by China went up by 10 to 25% depending on the crops, this does not mean that the U.S. exports automatically face the equivalent increases in the tariffs. In fact, as China discourages the U.S. exports, they get diverted to other markets with different tariffs (Hubbs, 2018; Taheripour and Tyner, 2018). As a result, the final export-volume weighted average tariff will tend to be lower than the net tariff imposed by China. The resulting tariff will depend on the time horizon under consideration. In the short run, the weighted-average tariffs will be affected only by the readjustment of trade flows. We use the GTAP model to predict the readjustment and thus the weighted-average tariffs.

The availability of data on the county-level cash rents limits our study to the period 2008–2017. By the beginning of this period, most of the tariff reductions agreed upon during the WTO Uruguay Round were already in place. Likewise, agricultural trade within North America was mostly liberalized. This limits the variation of tariffs across destination markets to recent few consequential events. Chiefly among these is the U.S.—Korea Free Trade Agreement, that went into force in early 2012 (Baylis, Coppess, and Xie, 2017). Another important source of dynamism in tariffs during this period is China's increased consumption of U.S. commodities (Gale, Hansen, and Jewison, 2015). Despite the limited sample period, there still exist informative variations within and across the sample counties (see section 2 and figure 5).

The empirical evidence on the effects of market accessibility for the U.S. agriculture is relatively scarce, with the notable exception of Donaldson and Hornbeck (2016), which uses railroad expansion during 1870–1890 as a proxy for changes in domestic and foreign market access to estimate the effects of freer trade on U.S. land values. A potential factor explaining the lack of empirical assessment of trade liberalization on the returns to the factors employed by agriculture is the difficulty of linking geographically disaggregated economic units, such as counties, to trade shocks faced by the U.S. as a whole.

A recent and influential growing literature have made enormous progress refining the use of "shift-share" designs (e.g. Bartik, 1991; Autor, Dorn, and Hanson, 2013; Kovak, 2013; Jaeger, Ruist, and Stuhler, 2018; Adão, Kolesár, and Morales, 2019), which consist on obtaining measures of within-country spatially disaggregated variation in shocks which are only observed at the country level (e.g., trade or immigration), using initial sectoral employment shares. The theoretical underpinnings of this strategy were greatly improved by Kovak (2013), who developed theoretically-consistent aggregation schemes based on the specific factor model of Jones (1975). Note that these studies are concerned with the effects of reducing owns tariffs (e.g. Topalova, 2010; Kovak, 2013) or importing more from China (e.g. Autor, Dorn, and Hanson, 2013), on local labor markets. These recent developments motivate our proposed estimation approach.

2 Data

2.1 Data Description

We use annual county-level data of cash rents for non-irrigated fields in the U.S. from 2008 to 2014 and from 2016 to 2017 collected by the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (U.S. Department of Agriculture, National Agricultural Statistics Service, 2018). Note that NASS did not conduct the cash rent survey in 2015. We choose the counties with more than one year of observations from the NASS cash rent survey, which leads to 2,534 counties. The per acre cash rental rates are adjusted by the producer price index with 1982 being base year (Bureau of Labor Statistics, 2018).

To connect the tariffs imposed on the U.S. exports by importing countries to the changes in the farmland rental rates, we focus on seven field crops that the U.S. exports: barley, corn, oats, sorghum, soybeans, upland cotton, and wheat. We hypothesize that the tariffs faced by the U.S. exports of these crops affect the cash rental rates of non-irrigated fields. To measure the importance of each crop for a given county, we compiled the planted acreage data from NASS survey data. Since the NASS survey data combines counties in a district with small numbers of planted acreages into a single observation per year, we do not observe the planted acreages for all seven crops in all of our sample counties. For counties with missing values for the planted acreages, we treat them as zeros. We also subtract the irrigated planted acreage from the planted acreage to focus on non-irrigated farmlands. We also obtain the annual production values by crop from the NASS survey data.

By combining the compiled planted acreage data with the county-level total cropland data from the two rounds of the Census of Agriculture (U.S. Department of Agriculture, National Agricultural Statistics Service, 2014), we compute the shares of each crop. We subtract the irrigated cropland that was harvested from total cropland and then use this as the denominator—representing total non-irrigated cropland area—for calculating the crop shares. We observe some shares greater than one, which can be due to the discrepancy between the Census and the survey data and in such cases we replace them with one. We also use the weather data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) and compute the growing degree days (GDDs) and the heating degree days (HDDs) using daily data from April to September following Schlenker and Roberts (2009). The temperature thresholds for GDDs are 10 and 30 degrees Celsius and 30 degree Celsius for HDDs.

We obtain the tariff and trade volume data from the World Integrated Trade Solution (WITS) database developed by the World Bank (World Integrated Trade Solution, World Bank, 2019) that enables users to run queries to obtain relevant trade and tariff data from UNCTAD Trade Analysis Information System (TRAINS) and UNSD Commodity Trade (UN Comtrade). We extract the importer-exporter pair level data for the seven field crops using 4-digit Harmonized Tariff Schedule (HS) codes (1001; 1003; 1004; 1005; 1007; 1201; 5201).

The TRAINS database does not necessarily include all relevant tariff lines. For example, preferential tariff rates are missing for Mexico in years 2011–2013 and 2015–2016 and TRAINS reports that the effectively applied tariffs (AHS) that Mexico applied to some of the U.S. imports are equal to the most-favored-nation tariff rates (MFN). However, it is not reasonable to assume that Mexico applied the MFN to the imports from the U.S. in those years since the U.S. and Mexico were in the NAFTA. Thus, in such cases, it is reasonable to assume that the preferential tariff rates are simply not reported. Therefore, if we observe any preferential tariff for a given reporter-partner pair for a given HS code in certain years but do not observe for the later years from the years with the preferential tariff, we replace the AHS with the preferential tariff from the most recent year. We also replace the AHS with the preferential tariff if both AHS and the preferential tariff are reported and the AHS is larger than the preferential tariff.

Also, the TRAINS database does not take account the Tariff-Rate Quota (TRQ) implementation and generally reports the out-of-quota tariff rates. We believe that the out-of-quota tariff rates are reasonable for the most of countries since quotas are usually binding or close to be filled for the seven crops except for China. Chinese TRQs have not been filled for corn and wheat and the fill rates have been quite low (Chen, Villoria, and Xia, forthcoming). Thus, for Chinese imports of U.S. corn and wheat we replace with the in-quota rate of 1%. Finally, there are missing years in the TRAINS and UN Comtrade database for some of the importer-exporter pairs. We impute the missing years by using the average of the consecutive years around the missing years if they are not missing. Our results are robust with respect to this imputation and we report the results without the imputation in Appendix A.

2.2 Data Exploration

Figure 1 shows the 2008–2017 average of the cash rental rates of non-irrigated farmlands for each county. As expected, the counties in the Corn Belt states (e.g. Illinois, Indiana, Iowa) have higher rents on average compared other counties. Figure 2 shows the percentage changes between the average of 2008–2012 and the average of 2013–2017. While the Corn Belt counties have high cash rental rates on average throughout the sample period, the counties located in North and South Dakotas, Nebraska, Minnesota, Wisconsin, Michigan, and Ohio experienced substantial increases in their cash rental rates.

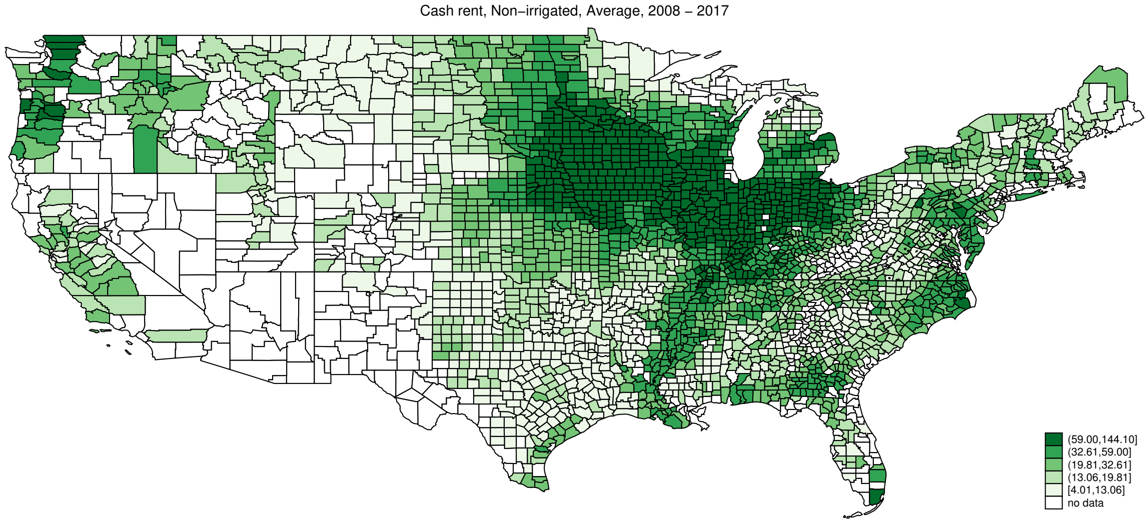

Figure 1: Cash rent, non-irrigated, PPI adjusted USD/acre (1982=100), average, 2008–2017

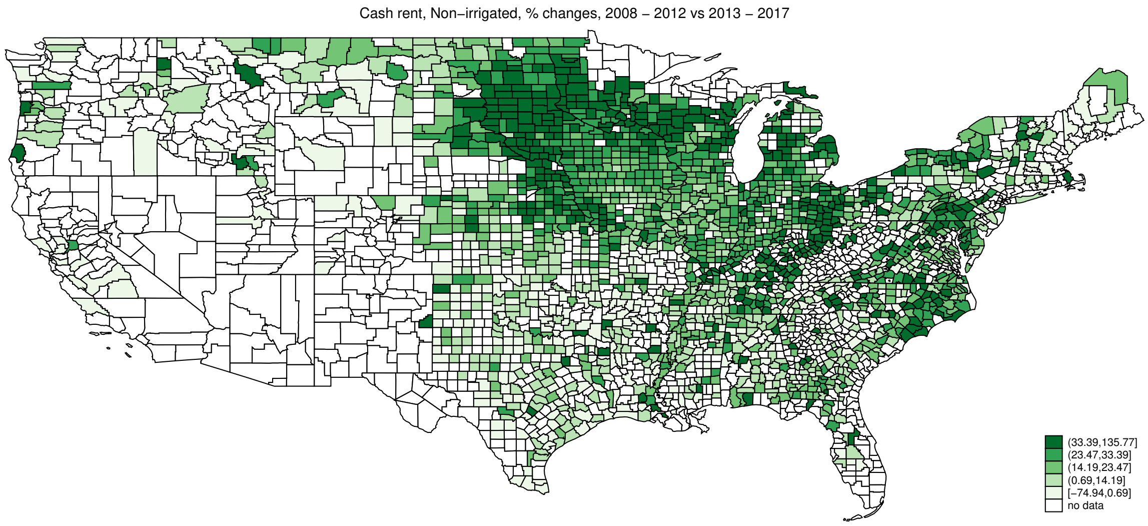

Figure 2: Cash rent, non-irrigated, % changes, 2008–2012 vs 2013–2017

Figure 3 presents the trend of nominal and real cash rents distributions from 2008 to 2017. The average and the dispersion of nominal cash rents experienced a drop from 2008 to 2009 and increases steadily afterwards. Real cash rents decreased until 2011 and started to increase since. Note that the number of observations is smaller in 2008 compared to other years since rents were reported for a lot fewer counties in 2008 (1,236 counties in 2008 whereas other years have reported counties range from 2,159 to 2,240). One concern from the difference in the number of counties between 2008 and the other years is the attrition problem and thus, we conduct our main analyses when we exclude the 2008 data and results are robust (see Appendix A).

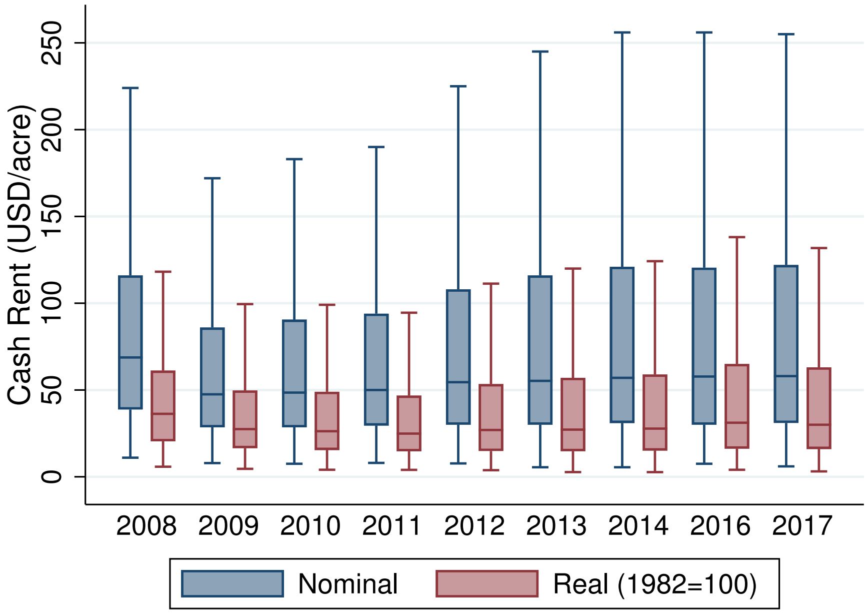

Figure 3: Boxplots of non-irrigated cash rents by year

Figure 4 shows the trends of the crop-specific tariffs faced by U.S exports computed as an average across export destinations weighted by the contemporaneous trade volume (the upper panel) or by the average trade volume from 2003 to 2007 (the lower panel) to each destination. Crop-specific tariffs have been decreasing over time. Note that the variations in the upper panel are due to either the reduction in the tariff rates imposed by the importing countries or changes in the trade flows whereas the variations in the lower panel are solely from the changes in the tariff rates.

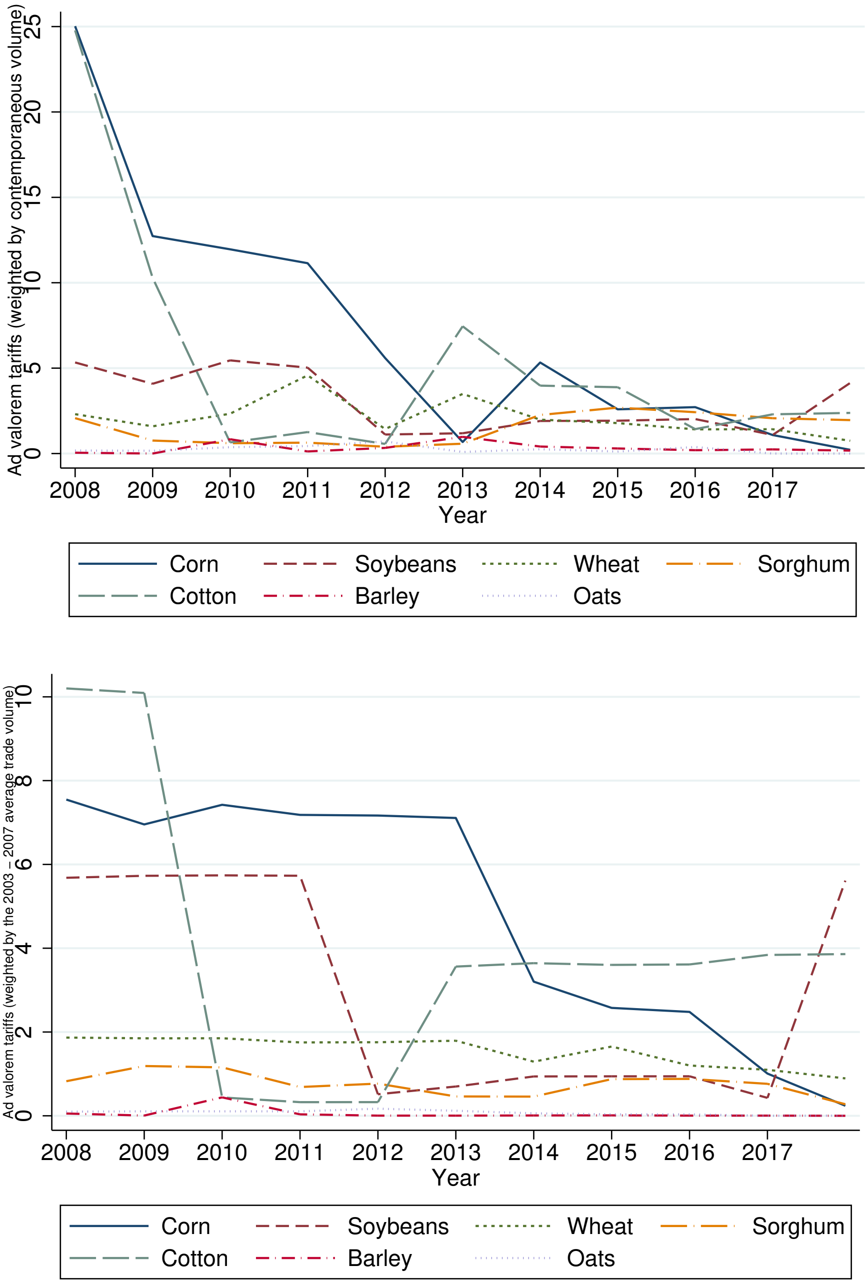

Figure 4: Trends in tariffs that U.S. field crop exports face (The upper panel uses the contemporaneous trade volume shares as the weights and the lower panel uses the average of 2003–2007 as the weights)

Finally, table 1 displays the summary statistics for the key variables including cash rents, crop shares, localized tariff exposures and weather variables for the full sample, the subsamples of 2008 - 2012 and of 2013 - 2107. As shown by figures 2 and 3, cash rents are greater during the last five years of the sample. Corn and soybeans have the largest shares among the seven field crops throughout the sample period accounting for about 20% of non-irrigated croplands in the sample counties.

To compute the localized tariff exposures, we consider the following three approaches (See section 3 for the detailed discussion on these approaches). The first approach is use contemporaneous export shares and contemporaneous crop shares to calculated the average tariff for each county. The second approach uses the contemporaneous export shares, but holds crop shares fixed at initial levels. The third approach holds the export shares and crop shares fixed at the initial levels. During the first five years, the average localized tariff exposures range from 3.0 to 3.7 % ad valorem equivalent and become smaller in the last five years with 1.0 – 1.2 % ad valorem equivalent.

Figure 5 shows the boxplots of tariff rates across commodities to illustrate the distribution across counties in each year using the three different approaches to calculate the localized tariffs, LT. While the overall trend of reductions in LT is consistent across the three different approaches, year-to-year variations differ. The two LT measures that uses the contemporaneous export share are relatively similar compared to the one with the export shares help constant at the initial period because the trade flows have a greater degree of variation compared to local crop shares.

Table 1: Descriptive statistics of county-level observations by year

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		2008 – 2012		2013 – 2017	
VARIABLES	Mean	SD	Mean	SD	Mean	SD
Nominal Cash Rent (USD/acre)	76.67	61.51	70.50	53.18	83.57	69.00
Real Cash Rent (USD/acre, PPI 1982=100)	39.65	31.54	37.09	27.72	42.51	35.10
Share of Barley	0.00395	0.0335	0.00397	0.0297	0.00392	0.0373
Share of Corn	0.195	0.206	0.203	0.204	0.185	0.208
Share of Cotton	0.0311	0.112	0.0305	0.111	0.0318	0.113
Share of Oats	0.00339	0.0144	0.00399	0.0157	0.00273	0.0128
Share of Sorghum	0.00781	0.0385	0.00815	0.0397	0.00744	0.0371
Share of Soybeans	0.184	0.203	0.186	0.196	0.183	0.211
Share of Wheat	0.0781	0.143	0.0846	0.145	0.0708	0.140
Contemp. Export and Crop Shares, LT_{it}	2.420	3.135	3.665	3.775	1.030	1.111
Contemp. Export and Initial Crop Shares, $\tilde{LT}_{it}$	2.457	3.108	3.706	3.748	1.062	1.033
Initial Export and Crop Shares, $\bar{LT}_{it}$	2.132	2.233	2.973	2.574	1.192	1.220
GDD	1,919	496.9	1,927	511.5	1,910	479.9
HDD	48.45	59.11	57.42	68.25	38.42	44.76
Precipitation	600.2	203.4	587.2	207.8	614.7	197.4
Number of Counties	2,534		2,478		2,511	
N	18,739		9,887		8,852	

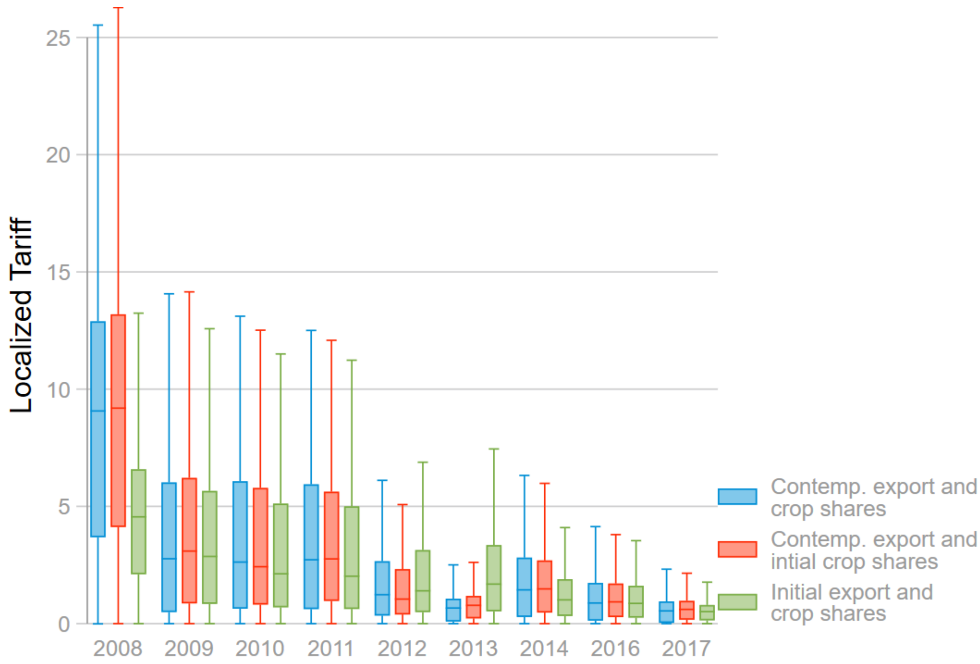

Figure 5: Boxplots of three alternative measures of localized tariffs by year

3 Model

3.1 Conceptual Model

To motivate our main empirical approach, we start with the following simple expression of crop-specific net profit function for county i and crop j, which can be represented as:

$$Profit_{ij} = p_j(\tau_j, \eta_j)q_j(X^*_{ij}, z_i) - WX^*_{ij} \quad (1)$$

where p_j and q_j are the price and the quantity produced, W is the vector of input prices, τ_j and η_j are the export tariff and the (non-tariff) price shifters, z_i is the vector of county-specific characteristics, and X^*_{ij} is the vector of optimal input uses, which are functions of p_j, z_i, and W. To avoid notational clutter, we omit the time subscript for now. We linearly approximate equation (1) as

$$Profit_{ij} = \alpha_0 + \alpha_1\tau_j + \alpha_2\eta_j + \Gamma W + z_i. \quad (2)$$

Assuming a competitive land rental market, we express the county average rental rate as the acreage-weighted average of crop-specific net profit functions, which is

$$
\begin{aligned}
Rent_i &= \frac{\sum_j (\alpha_0 + \alpha_1 \tau_j + \alpha_2 \eta_j + \Gamma W + z_i) A_{ij}}{\sum_j A_{ij}} \\
&= \sum_j (\alpha_0 + \alpha_1 \tau_j + \alpha_2 \eta_j + \Gamma W + z_i) S_{ij} \\
&= \alpha_0 + \alpha_1 \sum_j \tau_j S_{ij} + \alpha_2 \sum_j \eta_j S_{ij} + \Gamma W + z_i
\end{aligned} \tag{3}
$$

where A_{ij} is the planted acreage of crop j in county i, and S_{ij} is the share of planted acreage in total cropland for crop j in county i. Note that $\sum_j S_{ij} = 1$.

3.2 Econometric Model

Equation (3) leads to our main empirical equation of interest:

$$Rent_{it} = \beta_0 + \beta_1 LT_{it} + \Gamma X_{it} + \lambda_{1s} t + \lambda_{2s} t^2 + u_i + v_t + \varepsilon_{it} \tag{4}$$

where LT_{it} is the localized (ad valorem) tariff exposure, and X_{it} is the vector of other covariates including weather variables, and u_i and v_t are county and year fixed effects. We also include state-specific quadratic time trends to control for region-specific evolution of cash rents and LT over time. The parameter of interest is β_1, which is the effect of the localized tariff on the cash rents. We define the localized (ad valorem) export tariff rate for county i in year t as

$$LT_{it} = \sum_j \tau_{jt} \times S_{ijt} \tag{5}$$

where τ_{jt} is an aggregated tariff that is faced by the U.S. export of crop j in year t and S_{ijt} is the weight that represents the share of the planted acreage of crop j in county i and in year t divided by the total cropland (excluding irrigated land), i.e. $S_{ijt} = \frac{Planted\ Acreage_{ijt}}{Cropland_{it}}$. We also estimate equation (4) with the natural log of real cash rent as the dependent variable. Considering the possible correlations of the regressors and the error term within states and within years, we cluster the standard errors on state and on year (Cameron, Gelbach, and Miller, 2011).

The tariff and trade volume data from WITS are at the level of the pairs of importing and exporting countries. Therefore, we need to aggregate the pair-level data to the commodity level. We denote the ad valorem tariff rate imposed by importing country d for crop j in year t as τ_{jdt}. For τ_{jdt}, we use the effectively applied tariffs (AHS) that are the volume-weighted average at the HS code 4-digit level. We treat the domestic consumption as "export" to the U.S., $d = US$, with zero tariff, $\tau_{jUSt} = 0$, throughout the sample period. For crop j, in year t, the aggregated tariff rate for crop j in year t, τ_{jt}, is defined as

$$\tau_{jt} = \sum_{d} \theta_{jdt} \times \tau_{jdt} \tag{6}$$

where θ_{jdt} is the weight, which is based on the trade volumes imported by each country, i.e. $\theta_{jdt} = \frac{Imported\ Volume_{jdt}}{Total\ Production_{jt}}$.[1]

Estimating equation (4) where the localized tariff exposure is constructed by using contemporaneous shares, i.e. $LT_{it}(\theta_{jdt},\ S_{ijt})$, as weights is subject to endogeneity concerns. Any demand or supply shifters—denoted as η_j in equation (3)—will affect the cash rent and the crop shares simultaneously such that $Cov(S_{ijt},\ \varepsilon_{it}) \neq 0$, which implies $Cov(LT_{it},\ \varepsilon_{it}) \neq 0$. For example, the increased corn demand caused by the U.S. biofuel policy affects cash rents and crop shares simultaneously by changing profitability and promoting corn production. Unobserved supply and demand shocks for crops can also affect the import shares such that $Cov(\theta_{jdt},\ \varepsilon_{it}) \neq 0$. For example, a major drought in the U.S. in 2012 could have affected cash rents but it also increased the share of U.S. domestic corn consumption and reduced the corn-specific tariff, τ_{jt}, since greater weight is placed on the zero domestic tariff.

Our main identification strategy to deal with the endogeneity from the contemporaneous shares is to utilize a measure of the localized tariff constructed with initial shares as an instrument. The first stage regression that we estimate is

$$LT_{it} = \pi_0 + \pi_1 \bar{LT}(\theta_{jd0},\ S_{ij0}) + \pi_3 X_{it} + \pi_{4s} t + \pi_{5s} t^2 + \mu_i + \upsilon_t + e_{it}, \tag{7}$$

where $\bar{LT}(\theta_{jd0},\ S_{ij0})$ denotes the localized tariff constructed with initial trade volume shares $\theta_{jd0} = \frac{Imported\ Volume_{jd0}}{Total\ Production_{j0}}$ and crop shares $S_{ij0} = \frac{Planted\ Acreage_{ij0}}{Cropland_{i0}}$. The initial trade volume shares are calculated such that $Imported\ Volume_{jd0}$ and $Total\ Production_{j0}$ are the five-year average over the years 2003–2007. Similarly, the initial crop shares are calculated where $Planted\ Acreage_{ij0}$ is the five-year average over the years 2003–2007 and $Cropland_{i0}$ is the total cropland (excluding irrigated land) from the 2007 Census.

[1] Note that the annual production values reported by NASS are smaller than the total exports of UN Comtrade for some crops in some years. For such cases, we replace the annual production values with the total exports.

3.3 Identification Assumptions

Our empirical approach is motivated by the literature on Bartik instruments and shift-share designs (e.g. Bartik, 1991; Autor, Dorn, and Hanson, 2013; Kovak, 2013; Jaeger, Ruist, and Stuhler, 2018; Adão, Kolesár, and Morales, 2019). The core idea is to exploit plausibly exogenous shocks (i.e., crop-specific tariffs) on counties that are differentially exposed to the shocks (i.e., through crop shares). Adão, Kolesár, and Morales (2019) discuss the exclusion restriction in relationship to shift-share designs like our setting.

The key assumption for identification of our IV estimator is that crop-specific tariffs, τ_{jt}, which is measured as the weighted-average of τ_{jdt} by the initial trade shares, are independent of cash rent in the absence of the tariffs, conditional on the included controls (Adão, Kolesár, and Morales, 2019). This assumption is violated if crop-specific changes in tariffs are correlated with crop-specific non-tariff price shifters, i.e. $Cov(\tau_{jt}, \eta_{jt}) \neq 0$. One crop-specific price shifter during this period was ethanol demand. According to data from Economic Research Service (ERS), corn used for ethanol increased sharply from 2008 to about mid-2010 and then remained relatively stable afterwards (Economic Research Service, United States Department of Agriculture, 2019). Tariffs for corn decreased over the period (figure 4), but not necessarily in the same pattern as ethanol demand as corn tariffs decreased sharply from 2011 to 2013 (figure 6). Note that we also include state-specific quadratic time trends to control for region-specific evolution of cash rents and LT over time.

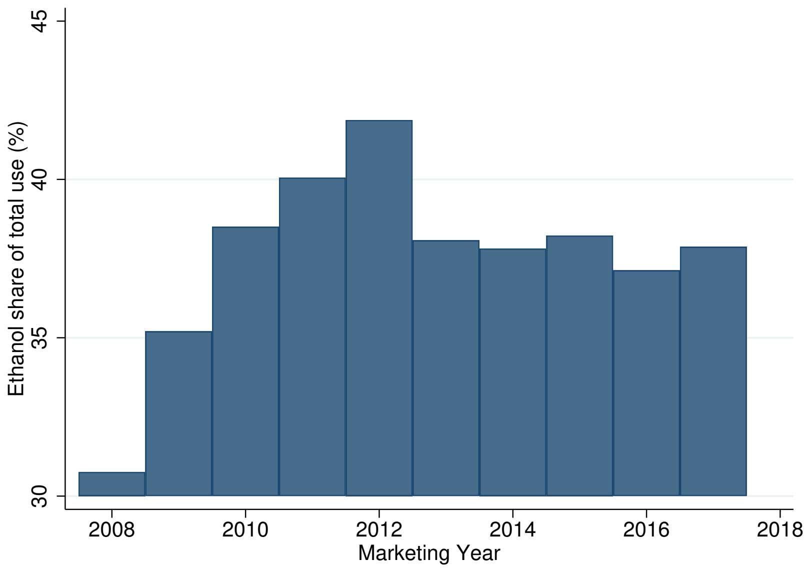

Figure 6: Trends in the share of ethanol use over the total corn production

Including county and time fixed effects is key to eliminating potential bias. For example, counties producing crops with higher tariffs could have unobserved biophysical characteristics that also affect rental rates. These biophysical characteristics are controlled for with county fixed effects. Changes in tariffs could also be influenced by macroeconomic factors that also affect all crop prices, but these are controlled for with year fixed effects.

The other assumption for our IV estimator to be unbiased is that the first-stage relationship with the instrument is sufficiently strong, i.e. $\pi_1 \neq 0$. This condition is trivial in our setting because much of the variation in localized tariffs is due to changes in crop-specific tariff rates that drives the variation in our instrument $\bar{LT}(\theta_{jd0},\ S_{ij0})$. The first-stage F statistics are greater than the rule-of-thumb threshold of 10 for testing "weak" IV (Stock, Wright, and Yogo, 2002) for all of our specifications.

3.4 Reduced-form Model

Alternatively, we also consider a reduced-form approach where we substitute the instrument directly into the second-stage equation:

$$Rent_{it} = \beta_0 + \beta_1 \bar{LT}(\theta_{jd0},\ S_{ij0}) + \Gamma X_{it} + \lambda_{1s} t + \lambda_{2s} t^2 + u_i + v_t + \varepsilon_{it}. \tag{8}$$

Assumptions for equation (8) to be unbiased are similar to the assumptions of our IV model (Adão, Kolesár, and Morales, 2019). We also consider the measure of LT that uses the contemporaneous export shares, but holds crop shares fixed at initial levels (denoted as $\tilde{LT}(\theta_{jdt},\ S_{ij0})$). We also estimate results with the natural log of reals rent as the dependent variable.

A key difference between the IV and the reduced-form models is the interpretation of β_1. For example, consider the impact of an increase in the tariff by country A. The coefficient in the IV model uses contemporaneous shares, so estimating the impact of country A's tariff on rental rates should also account for how shares adjust when calculating the new LT. The coefficient in the reduced-form model does not account for changes in shares to calculate the localized tariff, so estimating the impact of country A's tariff would simply require calculating the new LT with the initial shares. The difference leads to two distinct approaches to compute the LT that incorporates the 2018 Chinese retaliatory tariffs in section 6.

4 Estimated Incidence of Tariff Changes on Farmland Rental Rates

Table 2 reports the estimated results of equations (4) and (8). Panel A reports the results from the estimations with real cash rents as the dependent variables and panel B reports the results with the natural log of the dependent variable as the dependent variables. In Panel A, the first two columns report the estimated coefficient of β_1 of equation (4) followed by the two other columns with the estimated coefficient of β_1' of equation (8) where the dependent variables are in levels. As discussed in the earlier section, we estimate equation (4) using an IV estimation. The first-stage F statistics of the IV estimation is 61.59, which is far exceeding the rule-of-thumb threshold of 10 for testing "weak" IV (Stock, Wright, and Yogo, 2002).

Both columns (1) and (2) report a positive and significant effect of the localized tariff exposure measured by the contemporaneous share. Column (2), which is the IV estimate, reports the estimated coefficient that is more negative than that of column (1). We suspect that the variable, $LT_{it}(\theta_{jdt},\ S_{ijt})$, is positively correlated with the error term via θ_{jdt} or S_{ijt}. For example, if there are outward shifts of the demand from some destination countries with relatively higher tariffs, LT_{it} would increase but also the shifts would lead to better profitability, and thus, possibly higher rents (thus, possibly, $Cov(\theta_{jdt},\ \varepsilon_{it}) > 0$). Similarly, $LT_{it}(\theta_{jdt},\ S_{ijt})$, can be positively correlated with the error term if croplands in a county are moving toward to a crop with higher tariff exposures, independently from tariff changes but due to other factors that lead to better profitability (i.e. $Cov(S_{ijt},\ \varepsilon_{it}) > 0$).

The increase in the magnitude of the estimated coefficient of LT_{it} is consistent across the two specifications of the dependent variable. The estimated coefficient reported in column (2) of panel A indicates that an one percent point increase in the localized tariff exposure (ad valorem equivalent) leads to about 2 real USD reduction in the cash rents, which is about 5.3% of the overall average (4.6% of the 2017 average). Similarly, the log specification (the estimated coefficient in column (2) of panel B) indicates that the cash rent decreases by about 2.6% as the localized tariff exposure increases by a percent point.

Table 2: Effects of the localized tariff exposure on cash rents (non-irrigated) (Note: Standard errors are clustered at the state and year levels)

Panel A: Real Cash Rents (PPI adjusted USD/acre)

	(1)	(2)	(3)	(4)
	FE	FE-IV	FE	FE
VARIABLES	Real Cash Rent	Real Cash Rent	Real Cash Rent	Real Cash Rent
Contemp. shares, LT_{it}	-1.226***	-2.116***		
	(0.208)	(0.493)		
Contemp. export and init. crop shares, $\tilde{LT}_{it}$			-1.518***	
			(0.281)	
Init. shares, $\bar{LT}_{it}$				-1.964***
				(0.546)
Observations	18,739	18,739	18,739	18,739
First stage F	NA	61.59	NA	NA
Weather Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes

Panel B: Ln of Real Cash Rents (PPI adjusted USD/acre)

	(1)	(2)	(3)	(4)
	FE	FE-IV	FE	FE
VARIABLES	ln(Real Cash Rent)	ln(Real Cash Rent)	ln(Real Cash Rent)	ln(Real Cash Rent)
Contemp. shares, LT_{it}	-0.0134***	-0.0257***		
	(0.00316)	(0.00470)		
Contemp. export and init. crop shares, $\tilde{LT}_{it}$			-0.0165***	
			(0.00390)	
Init. shares, $\bar{LT}_{it}$				-0.0239***
				(0.00471)
Observations	18,739	18,739	18,739	18,739
First stage F	NA	61.59	NA	NA
Weather Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes

Columns (3) and (4) report the results from the reduced-form regressions of equation (8), which use the localized tariff measures using the initial crop shares and the contemporaneous export shares, and using the initial crop and export shares as the key explanatory variables. Again, the results are consistent across the two dependent variables. In both panels, the estimated coefficients of column (3) have smaller magnitude than those of column (4), which suggests that contemporaneous export shares lead to a positive correlation between the localized tariff exposure and the error term. The magnitude of the coefficients in column (4) is similar to those in column (2), which are the IV estimates.

5 Fisher's Randomization Tests

Given potential correlations within each state and within each year, we cluster the standard errors at state- and year-level following Cameron, Gelbach, and Miller (2011). Although we believe that the two-way clustering provides us an appropriate statistical inference, the variance-covariance matrix of error can have more complex structure than what multi-way clustering can capture (e.g. Adão, Kolesár, and Morales, 2019; Barrios et al., 2012).

Therefore, we conduct Fisher's randomization test (FRT, Fisher, 1960) based on a similar permutation approach as that of Hsiang and Jina (2014). More specifically, we provide alternative p-values using the following two types of permutation samples: i) permutation across counties (cross-sectional permutations) and ii) permutation across years (time-series permutations). Using these permutation samples, we re-estimate equation (8), obtain the distributions of the estimated coefficients for the localized tariff variable (i.e. $\hat{\beta}_1$) and the associated t-statistics, and then compute the p-values associated with the estimated coefficient and the t-statistic from the actual observations. The test based on the cross-sectional permutations checks the possibility of coincidental statistical significance of the main results from unobservable time-specific shocks. Similarly, the test based on the time-series permutations checks whether the main results are driven by unobservable county-specific factors.

For the cross-sectional permutations, we first shuffle $\mathbf{S}_{i0}$, which is the vector of initial crop shares, S_{ij0}, across counties. We then merge the outcome variable, the tariff variables, and the weather covariates with the shuffled set of $\mathbf{S}_{i0}$. With this new dataset, we compute $\bar{LT}(\theta_{jd0},\ S_{ij0})$ and estimate equation (8). We conduct 5,000 iterations of these steps. For the time-series permutations, we shuffle $\mathbf{T}_t$, which is the vector of crop-specific tariffs (initial export share weighted), $\bar{\tau}_{jt}(\theta_{jd0})$, across years. In order to have sufficient number of underlying permutations, we shuffle $\mathbf{T}_t$ across years. The rest of the estimation procedure is equal to that of the cross-sectional permutations. Note that the two permutation approaches are equivalent to drawing 5,000 pseudo-sample datasets from all possible permutations. For the cross-sectional permutations, the number of possible permutations is $2^{2,535}$ given 2,535 counties and for the time-series permutations, the number is 2^{15} given 15 years from 2003 – 2017.

Figure 7 presents the distributions of the estimated coefficients and the associated t-statistics from the cross-sectional and the time-series permutations. The upper two density plots are based on the cross-sectional permutations and the lower plots are based on the time-series permutations. The left plots are the distributions of the estimated coefficients and the right plots are the distributions of the estimated t-statistics. We also report the empirical p-values for the estimated coefficient, -1.96 (Column (4), Panel A, table 2), and the t-statistic, -3.60, which is the estimates from the actual observations.

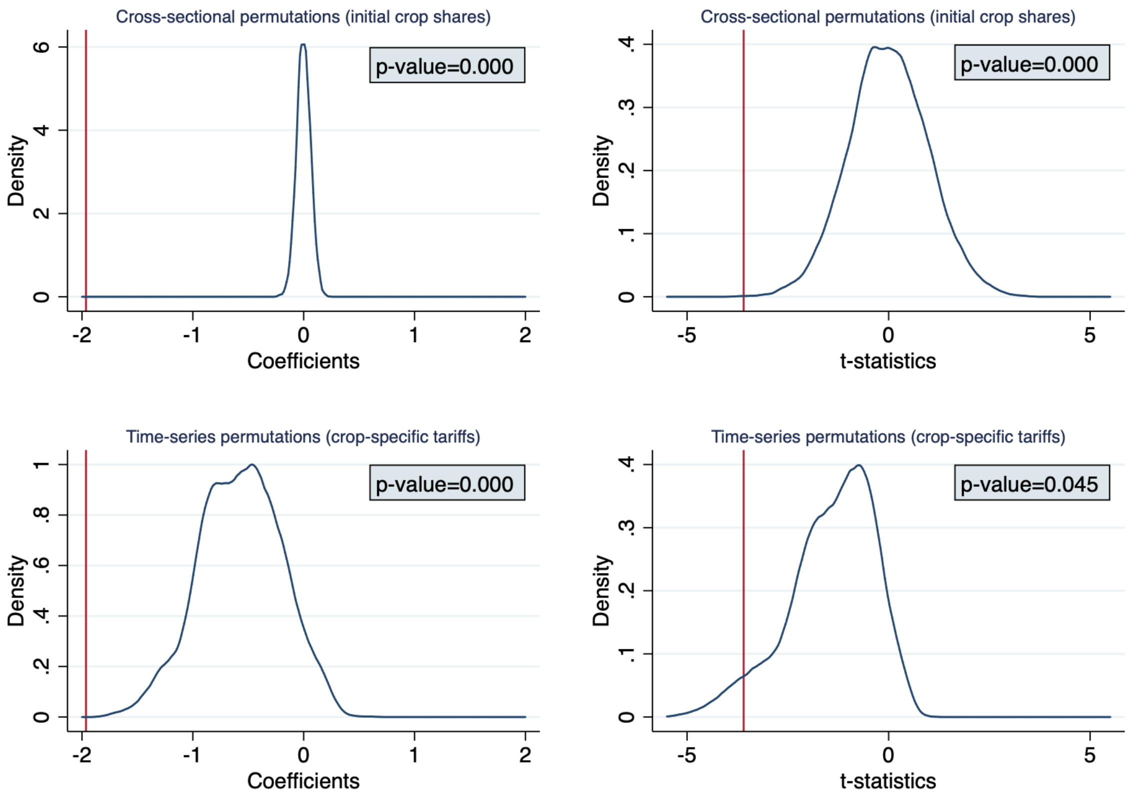

Figure 7: Distributions of estimated coefficients and t-statistics from different permutation samples (Note: The density plots are based on 5,000 iterations. The p-values are empirical p-values–for the coefficients, we compute $Prob(\hat{\beta}_1 < -1.96)$ where -1.96 is the estimated coefficient from the actual observation and for the t-statistics, we compute $Prob(t < -3.60)$ where -3.60 is the t-statistic from the actual observation. The red solid lines represent the estimated coefficient and the t-statistic from the actual observations.)

Overall, our main result and the rejection of the null of zero tariff effect remain robust. The distributions of the estimated coefficients indicate that neither unobservable time-specific nor county-specific factors are driving the main result and its statistical significance. The empirical p-values from the distributions of cross-sectional and time-series permutations both are approximately zero (figure 7, the left panel). Alternatively, we can also compute Fisher's exact p-values of FRT from the distributions of the t-statistics. With slightly higher p-value for the time-series permutations, the both distributions have the p-values lower than 5%. We speculate that the relatively high p-value for the time-series permutations is due to the small number of years. However, even with the Fisher's exact p-values, our result remains robust.

6 Predicted Impacts of the 2018 Chinese Retaliatory Tariffs on the U.S. Agricultural Exports

In order to place the estimated effects in the context of the 2018 trade war between the U.S. and China, we provide several estimates of the predicted impact of Chinese retaliatory tariffs on the U.S. exports. In July 2018, in response to the implementation of U.S. tariffs on Chinese products, China declared to increase the ad-valorem tariffs on the U.S. agricultural products. Table 3 summarizes the tariff changes for the seven field crops.

Table 3: 2018 Chinese retaliatory tariffs on the U.S. exports of the seven field crops (source: Regmi (2019))

Product	MFN	September 2018	Note
Barley	3%	3%	
Corn	1%	26%	In-quota rates
Cotton	1%	26%	In-quota rates
Oats	20%	30%	
Sorghum	2%	27%	
Soybeans	3%	28%	
Wheat	1%	26%	In-quota rates

Although a sudden increase in tariffs is bound to drive a readjustment in trade flows, first, we assume that there is no trade diversion and estimate the impact of the nominal increase in the Chinese tariffs on the U.S. exports. In order to compute the change in the localized tariff exposure, we use the following equation:

$$\Delta_{China}\bar{LT}_i = \sum_j \left(\theta_{j\ China\ 0} \times (\tau_{j\ China\ 2018} - \tau_{j\ China\ 2017})\right) \times S_{ij0} \tag{9}$$

where $\theta_{j\ China\ 0}$ is the initial share of Chinese import, measured by using the average of 2003–2007, $\tau_{j\ China\ 2017}$ and $\tau_{j\ China\ 2018}$) are the Chinese tariffs imposed on the U.S. export of crop j before and after the retaliation, and S_{ij0} is the initial crop share in county i. The difference, $\theta_{j\ China\ 0} \times (\tau_{j\ China\ 2018} - \tau_{j\ China\ 2017})$, is reported in the first column table 4 by crop. For the no trade diversion scenario, we utilize the estimated coefficient of the reduced-form estimation, which utilizes the localized tariff exposure measured by using the initial export and crop shares. In other words, to predict the effect of the computed $\Delta_{China}\bar{LT}_i$, we use the estimated β_1' of column (4) in table 2.

Table 4: Estimated changes in crop-specific tariffs caused by the 2018 Chinese retaliatory tariffs on the U.S. exports

Product	No trade volume reallocation (Weighted by the initial export shares)	Trade volume reallocation (Weighted by the GTAP estimates)
Barley	0%	0%
Corn	0.0018%	0.17%
Cotton	7.63%	3.88%
Oats	0.000035%	0.17%
Sorghum	0%	0.17%
Soybeans	3.92%	4.03%
Wheat	0.54%	0.27%

However, trade volumes do reallocate with respect to their destinations as responses to sudden changes in tariff rates. In order to capture such reallocation, we use the GTAP model (Hertel, 1997) to calculate the changes in trade volumes following an increase in China's tariffs reported in table 3. The GTAP model is an applied general equilibrium model commonly used to evaluate trade policies. The model assumes that producers operate under constants returns to scale and is based on the standard framework of simultaneous utility and profit maximization. On the trade side, the model uses the so-called Armington assumption (Armington, 1969), whereby products are differentiated by place of origin.

For the trade volume adjustment scenario, we use the estimated changes from the simulated results of the GTAP model, which consider the reallocation in trade volumes to each destination. The second column in table 4 reports the estimated changes from the GTAP model. Similar to the no trade diversion scenario, we compute

$$\Delta_{China}LT_i = \sum_j \left(\sum_d (\hat{\theta}_{jd2018}\tau_{jd2018} - \theta_{jd2017}\tau_{jd2017}) \times S_{ij2017} \right). \tag{10}$$

where $\hat{\theta}_{jd2018}$ is the estimated shares of the trade volumes as responses to the Chinese retaliatory tariffs. The estimated changes, i.e. $\sum_d (\hat{\theta}_{jd2018}\tau_{jd2018} - \theta_{jd2017}\tau_{jd2017})$, are reported in the second column of table 4. We then compute the effect of $\Delta_{China}LT_i$ using the estimated β_1 of equation 4 via the IV estimation.

Table 5 reports the results from the two scenarios, no adjustment in trade volumes and trade volume adjustment based on Armington assumption via the GTAP model. Interestingly, the two scenarios predict similar magnitudes of the reductions due to the Chinese retaliatory tariffs. The percentage reductions are estimated based on the estimations with the natural log of the cash rents as the dependent variable and the nominal reductions are based on the estimation with the cash rents as the dependent variable. The average of the predicted reductions ranges from 2.33 to 2.45% or from 3.71 to 3.91 nominal USDs.

Table 5: Summary of counterfactual predictions

VARIABLES	(1) Mean	(2) SD	(3) Min	(4) Max
Nominal reduction (no trade adjustment)	3.714	4.383	0	36.05
Percentage reduction (no trade adjustment)	2.331	2.751	0	22.62
Nominal reduction (GTAP)	3.906	4.077	0	32.94
Percentage reduction (GTAP)	2.451	2.559	0	20.68
Number of counties	2,240			

Figures 8 and 9 report the spatial patterns of the predicted reductions in the cash rents caused by the Chinese retaliatory tariffs. Figure 8 show the predicted reductions based on the reduced-form estimation and the nominal changes in the tariffs faced by the U.S. products and figure 9 displays the predictions based on the IV estimation and the GTAP estimates of the changes in the localized tariff exposure. As expected, areas with high shares of cotton or soybeans had larger predicted reductions. Note that the subtle difference in the spatial patterns between the two figures is from the difference in the use of the contemporaneous or initial crop shares.

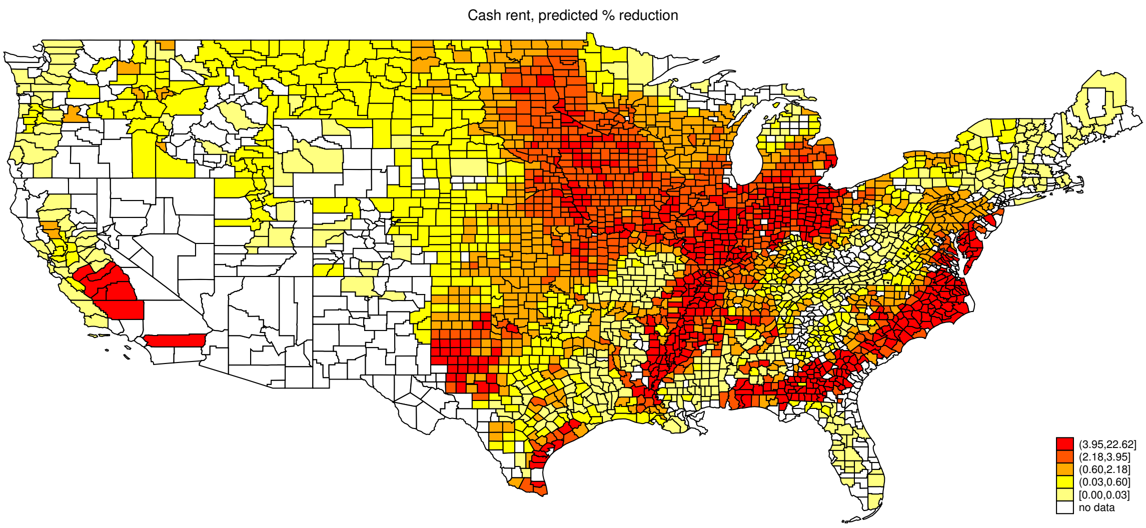

Figure 8: Cash rent, predicted percentage reductions, no trade diversion

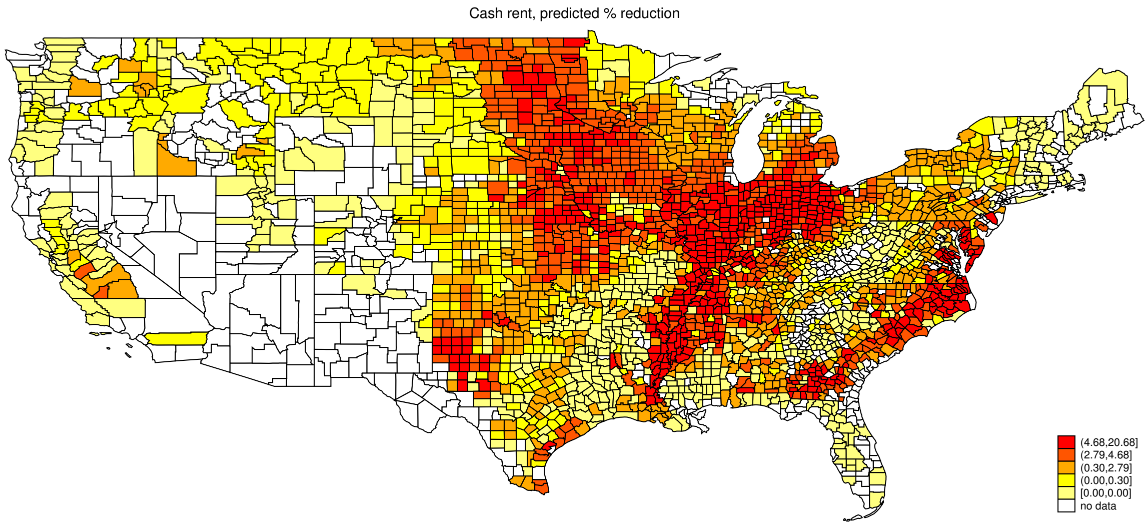

Figure 9: Cash rent, predicted percentage reductions, considering trade diversion

7 Alternative Specifications

Our main estimations leverage the variations in the tariffs throughout the years and across destination countries. While we carefully construct the identification approaches to estimate equations (4) and (8), there are two remaining concerns. First, our estimates may not represent the average effect across years if there are long-run adjustments as responses to the current and potential changes in tariffs. Another potential threat for our main specification is that the level of tariffs in a particular year can be coincidentally correlated with the cash rents and the results are driven by that particular year. As the robustness checks for our main specifications, we consider two approaches that utilize the variations measured for different time windows.

7.1 Panel Long Difference Approach

We first consider Panel long difference approach (Panel LD) to examine whether the long-run response deviates from the panel FE estimates, which would capture relatively shorter-run effects. Thus, we implement the panel long-difference model (e.g. Burke and Emerick, 2016) by computing the five-year average of the variables in equation (4) for the years 2012 and 2017 and take the difference.

Thus, we estimate the following equation:

$$Rent_{i\,post2012} - Rent_{i\,pre2012} = \beta_0 + \beta_1(LT_{i\,post2012} - LT_{i\,pre2012}) + \Gamma(Z_{i\,post2012} - Z_{i\,pre2012}) + \varepsilon_{it} \tag{11}$$

where $Rent_{i\,post2012}$ and $Rent_{i\,pre2012}$ are the five-year averages of the county-average cash rents for the periods 2008–2012 and 2013–2017, and $LT_{i\,post2012}$ and $LT_{i\,pre2012}$ are the five-year averages of the localized tariff exposure measured by using the contemporaneous shares. Similar to our main specification, we estimate equation (11) by an IV estimation. We use the long difference of $\bar{LT}$, which is the localized tariff exposure measured by the initial shares, as the instrument for the long difference of LT. We also estimate the long difference version of the reduced-form regressions, i.e. the long difference version of equation (8).

Table 6 reports the results from the panel LD regressions. The first two columns report the results from estimating equation (11) with OLS and IV and the last two columns report the results from the reduced-form regressions using the two alternative measures of the localized tariff exposure. Overall, the results of table 6 are consistent with the main estimation results. Similar to table 2, we find that the magnitude of the estimated coefficient from the IV estimation is greater than that from the OLS estimation. The reduced-form results, columns (3) and (4), are also consistent with the main estimation results with the estimated coefficient of $\bar{LT}$ is more negative than those of LT or $\tilde{LT}$. An interesting finding is that the coefficients of the reduced-form estimation in table 6 are substantially more negative than those in table 2 whereas the results of the IV estimation are similar.

Table 6: Cash rent (non-irrigated) versus localized tariffs: Panel LD (Note: Standard errors are clustered at the state level)

VARIABLES	(1) FE Real cash rent	(2) FE-IV Real cash rent	(3) FE Real cash rent	(4) FE Real cash rent
Contemp. shares, LT_{it}	-1.961***	-2.140***		
	(0.266)	(0.296)		
Contemp. export and init. crop shares, $\tilde{LT}_{it}$			-2.046***	
			(0.341)	
Init. shares, $\bar{LT}_{it}$				-3.235***
				(0.451)
Observations	2,455	2,455	2,455	2,455
First stage F	NA	356.03	NA	NA
Weather Covariates	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

7.2 Shift-share Analysis by Year

Shift-share designs are useful in estimating the effects of shocks that vary across economic sectors, but that can only be measured for the country as a whole, such as immigration (e.g. Jaeger, Ruist, and Stuhler, 2018), the emergence of China as an exporter (e.g. Autor, Dorn, and Hanson, 2013), or Brazilian trade liberalization (e.g. Kovak, 2013), on spatially heterogeneous labor markets. These studies use local-level sectoral labor shares at the initial time periods of the studies to capture differences in exposure to the shocks stemming from heterogeneous patterns of specialization. When we focus on farmland cash rental rates, which is analogous to wages, the natural analog to labor shares across different sectors are land allocations across different crops that face different degrees of foreign market accessibility.

As a robustness check, we utilize the shift-share design to show that the tariff reduction shocks affect cash rental rates positively. To construct the shift-share design, we need to define the pre-shock "base period". The most noticeable trade-related event during the sample period is the U.S.—Korea Free Trade Agreement, which became effective in early 2012 (Baylis, Coppess, and Xie, 2017). Given that the cash rent data start from 2008 but with relatively fewer counties being surveyed, we define the base period as the years from 2009 to 2011 and compute the annual tariff shocks based on such definition.

More specifically, we estimate the following regression equation for each year t:

$$\Delta Rent_{it} = \beta_0' + \beta_1' \Delta \bar{LT}_{it} + \Gamma \Delta Z_{it} + u_s + \varepsilon_{it} \tag{12}$$

where $\Delta Rent_{it} = Rent_{it} - \overline{Rent}_{i\,2009-2011}$, i.e. the change in cash rent in county i in year t from the average cash rent from 2009 to 2011. The tariff shocks are measure by

$$\Delta \bar{LT}_{it} = \sum_j \left(\sum_d (\tau_{jdt} - \tau_{jd\,2009-2011}) \times \theta_{jd\,2009-2011} \right) \times S_{ij\,2009-2011} \tag{13}$$

which is the weighted average of the changes in the tariffs in year t from the average tariffs from 2009 to 2011 weighted by the average export and crop shares from 2009 to 2011. The changes in weather covariates from the 2009–2011 average and state fixed effects are denoted by ΔZ_{it} and u_s.

The shift-share approach represented by equation (13) isolates the effect of tariff shocks on cash rental rates from the effects from changes in local crop production patterns. By fixing the export and crop shares at the levels in the base period of the analysis, we limit the confounding effect from the changes in crop production patterns and yet, exploit the spatial variations that stem from the different degrees of exposure to the changes in crop-specific tariffs. As reported in table 7, we find that the results are robust.

Table 7: Estimates from the shift-share design (Note: The base period is 2009–2011. Standard errors are clustered at the state level.)

VARIABLES	(1) Year 2012 Rent Change	(2) Year 2013 Rent Change	(3) Year 2014 Rent Change	(4) Year 2016 Rent Change	(5) Year 2017 Rent Change
Tariff Shock	-1.219***	-4.395***	-2.513***	-3.108***	-1.987***
	(0.356)	(0.844)	(0.382)	(0.389)	(0.271)
Observations	2,115	2,132	2,164	2,147	2,161
Weather Covariates	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

8 Discussion and Concluding Remarks

We find that the changes in nominal tariffs in destination markets have substantial effects on land rents. These results are robust to different specifications that try to minimize confounding effects due to the adjustment of both the crop and export destination portfolios as tariffs in destination markets change over time. The back-of-the-envelope estimate of the elasticity of the cash rents to changes in the localized tariffs from our panel estimates ranges from -0.015 to -0.028, so that an increase in the localized tariffs by 1% reduces land rents by 0.015–0.028%.[2] At the outset, we recognize that nominal tariffs are an incomplete measure of trade liberalization as it ignores the tariffs faced by other countries competing in the same destination. The fact that our main source of identifying variation is from free trade agreements negotiated after worldwide episodes of multilateral tariff reductions (i.e., the adoption of the WTO Agreement of Agriculture at the culmination in 1995), partially alleviates this concern.

Still, we recognize that it is possible that the countries to which the U.S. exports the most, were lowering their tariffs to other countries at the same time that they were lowering their tariffs to other countries. This would attenuate our parameter estimates if tariffs to enter the same destination would move together across all the exporting destinations and the price differentials

[2]These are from the back-of-the-envelope calculation of (2.12/43.04)/(1/0.57) and 0.026/(1/0.57) based on the 2017 values, where 2.12 and 0.026 are from column (2) of panels A and B in table 2, respectively.

across exporters would vanish. Including the variation in tariffs faced by the U.S. vis-à-vis the variations in tariffs faced by U.S. competitors is part of our future research. Yet, our estimates are useful to inform trade policy-makers and negotiators about the potential gains and losses accruing to the agricultural sector by negotiation preferential tariffs and likely to serve as lower bounds.

Likewise, as demonstrated in the paper, these estimates are also useful for the evaluation of the effects of unilateral losses of market access. Our estimates indicate that a naïve evaluation of the effects of the retaliatory tariffs imposed by China on U.S. field crop exports would cause large declines in land rents, particularly, and not surprisingly, in the counties where cotton and soybeans are the dominant crops.

References

Acemoglu, D., D. Autor, D. Dorn, G.H. Hanson, and B. Price. 2015. "Import Competition and the Great US Employment Sag of the 2000s." *Journal of Labor Economics* 34:S141–S198.

Adão, R., M. Kolesár, and E. Morales. 2019. "Shift-Share Designs: Theory and Inference*." *The Quarterly Journal of Economics*, 08, pp. .

Armington, P.S. 1969. "A theory of demand for products distinguished by place of production." *Staff Papers* 16:159–178.

Autor, D.H., D. Dorn, and G.H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *The American Economic Review*, pp. 2121–2168.

Barrios, T., R. Diamond, G.W. Imbens, and M. Kolesár. 2012. "Clustering, spatial correlations, and randomization inference." *Journal of the American Statistical Association* 107:578–591.

Bartik, T.J. 1991. "Who benefits from state and local economic development policies?", pp. .

Baylis, K., J. Coppess, and Q. Xie. 2017. "Reviewing the U.S.-Korea Free Trade Agreement • Farmdoc Daily."

Beckman, J., J. Dyck, and K. Heerman. 2017. *The Global Landscape of Agricultural Trade, 1995-2014*. No. 181 in Economic Information Bulletin, Washington D.C.: United States Department of Agriculture, Economic Research Service.

Bureau of Labor Statistics. 2018. "BLS Producer Price Index." Retrieved from https://www.bls.gov/ppi/.

Burke, M., and K. Emerick. 2016. "Adaptation to climate change: Evidence from US agriculture." *American Economic Journal: Economic Policy* 8:106–40.

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

Chen, B., N. Villoria, and T. Xia. forthcoming. "Tariff Quota Administration in China's Grain Markets: An Empirical Assessment." *Agricultural Economics*, pp. .

Donaldson, D., and R. Hornbeck. 2016. "Railroads and American Economic Growth: A "Market Access" Approach." *The Quarterly Journal of Economics* 131:799–858.

Economic Research Service, United States Department of Agriculture. 2019. "U.S. Bioenergy Statistics." Retrieved from https://www.ers.usda.gov/data-products/us-bioenergy-statistics/.

FAS. 2018. "U.S. Agricultural Exports Pre- and Post- Trade Agreements — USDA Foreign Agricultural Service." https://www.fas.usda.gov/data/us-agricultural-exports-pre-and-post-trade-agreements.

Fisher, R.A. 1960. *The design of experiments.*. 7th Ed, Oliver and Boyd. London and Edinburgh.

Gale, F., J. Hansen, and M. Jewison. 2015. "China's Growing Demand for Agricultural Imports."

Hertel, T.W. 1997. *Global Trade Analysis: Modeling and Applications*. Cambridge, MA: Cambridge University Press.

Hsiang, S.M., and A.S. Jina. 2014. "The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones." Working paper, National Bureau of Economic Research.

Hubbs, T. 2018. "Soybean Exports since the Onset of Tariffs • Farmdoc Daily."

Jaeger, D.A., J. Ruist, and J. Stuhler. 2018. "Shift-Share Instruments and the Impact of Immigration." *NBER Working Paper*, pp. .

Jiang, H. 2016. "Free Trade Agreements and U.S. Agriculture — USDA Foreign Agricultural Service."

Jones, R.W. 1975. "Income Distribution and Effective Protection in a Multicommodity Trade Model." *Journal of Economic Theory* 11:1–15.

Katz, L.F., and D.H. Autor. 1999. "Chapter 26 - Changes in the Wage Structure and Earnings Inequality." In O. C. Ashenfelter and D. Card, eds. *Handbook of Labor Economics*. Elsevier, vol. 3, pp. 1463–1555.

Kovak, B.K. 2013. "Regional Effects of Trade Reform: What is the Correct Measure of Liberalization?" *American Economic Review* 103:1960–1976.

Krugman, P.R. 2000. "Technology, Trade and Factor Prices." *Journal of International Economics* 50:51–71.

Regmi, A. 2019. "Retaliatory tariffs and U.S. agriculture." CRS Report No. R45903, Congressional Research Service, Washington D.C., September.

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

Schnepf, R. 2017. "U.S. Farm Income Outlook for 2017." CRS Report No. R40152, Congressional Research Service, Washington D.C., Oct.

Stock, J.H., J.H. Wright, and M. Yogo. 2002. "A survey of weak instruments and weak identification in generalized method of moments." *Journal of Business & Economic Statistics* 20:518–529.

Taheripour, F., and W.E. Tyner. 2018. "Impacts of Possible Chinese 25% Tariff on U.S. Soybeans and Other Agricultural Commodities." *Choices* 33.

Topalova, P. 2010. "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India." *American Economic Journal: Applied Economics* 2:1–41.

U.S. Department of Agriculture, National Agricultural Statistics Service. 2014. "Census of Agriculture." Retrieved from https://quickstats.nass. usda.gov/.

—. 2018. "NASS QuickStat." Retrieved from https://quickstats.nass. usda.gov/.

USDA. 2019a. "Production, Supply and Distribution Online." http://goo.gl/RPq9Ls.

—. 2019b. "USDA ERS - U.S. Agricultural Trade at a Glance." https://www.ers.usda.gov/topics/international-markets-us-trade/us-agricultural-trade/us-agricultural-trade-at-a-glance/.

World Integrated Trade Solution, World Bank. 2019. "World Integrated Trade Solution." Retrieved from https://wits.worldbank.org/WITS/WITS/Restricted/Login.aspx.

Appendix: Results from Alternative Samples

Estimation results without imputing missing years in tariff and trade data

Table A.1: Effects of the localized tariff exposure on cash rents (non-irrigated) (Note: Standard errors are clustered at the state and year levels)

Panel A: Real Cash Rents (PPI adjusted USD/acre)

VARIABLES	(1) FE Real Cash Rent	(2) FE-IV Real Cash Rent	(3) FE Real Cash Rent	(4) FE Real Cash Rent
Contemp. shares, LT_{it}	-1.250***	-2.067***		
	(0.225)	(0.577)		
Contemp. export and init. crop shares, $\tilde{LT}_{it}$			-1.542***	
			(0.305)	
Init. shares, $\bar{LT}_{it}$				-1.490**
				(0.505)
Observations	18,739	18,739	18,739	18,739
First stage F	NA	37.83	NA	NA
Weather Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes

Panel B: Ln of Real Cash Rents (PPI adjusted USD/acre)

VARIABLES	(1) FE ln(Real Cash Rent)	(2) FE-IV ln(Real Cash Rent)	(3) FE ln(Real Cash Rent)	(4) FE ln(Real Cash Rent)
Contemp. shares, LT_{it}	-0.0142***	-0.0282***		
	(0.00365)	(0.00573)		
Contemp. export and init. crop shares, $\tilde{LT}_{it}$			-0.0175***	
			(0.00453)	
Init. shares, $\bar{LT}_{it}$				-0.0203***
				(0.00571)
Observations	18,739	18,739	18,739	18,739
First stage F	NA	37.83	NA	NA
Weather Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes

Estimation results excluding 2008

Table A.2: Effects of the localized tariff exposure on cash rents (non-irrigated) (Note: Standard errors are clustered at the state and year levels)

Panel A: Real Cash Rents (PPI adjusted USD/acre)

VARIABLES	(1) FE Real Cash Rent	(2) FE-IV Real Cash Rent	(3) FE Real Cash Rent	(4) FE Real Cash Rent
Contemp. shares, LT_{it}	-1.346***	-2.274***		
	(0.263)	(0.563)		
Contemp. export and init. crop shares, $\tilde{LT}_{it}$			-1.749***	
			(0.364)	
Init. shares, $\bar{LT}_{it}$				-1.904**
				(0.544)
Observations	17,501	17,501	17,501	17,501
First stage F	NA	86.21	NA	NA
Weather Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes

Panel B: Ln of Real Cash Rents (PPI adjusted USD/acre)

VARIABLES	(1) FE ln(Real Cash Rent)	(2) FE-IV ln(Real Cash Rent)	(3) FE ln(Real Cash Rent)	(4) FE ln(Real Cash Rent)
Contemp. shares, LT_{it}	-0.0163***	-0.0264***		
	(0.00358)	(0.00605)		
Contemp. export and init. crop shares, $\tilde{LT}_{it}$			-0.0209***	
			(0.00446)	
Init. shares, $\bar{LT}_{it}$				-0.0221***
				(0.00535)
Observations	17,501	17,501	17,501	17,501
First stage F	NA	86.21	NA	NA
Weather Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes