The Effects of U.S. Trade War on Socioeconomic Outcomes*

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Abstract

This paper investigates the short-run impact of the U.S. trade wars of 2018-19 on socioeconomic outcomes in the United States. Using monthly data from 2016 to 2019, we exploit the variation in the agricultural and manufacturing production levels of counties, and present evidence that counties that were exposed to higher levels of agricultural production in the pre-trade war shock period, exhibit higher levels of crimes, especially property crimes. Thus, we provide linkages between economic shocks and socioeconomic outcomes and show that trade shocks have such indirect distributional impacts even in the short-run.

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Keywords: trade war, crime, distributional impacts

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1 Introduction

The gains and losses of international trade are not evenly distributed. Large trade shocks like the 'China shock' have been found to have distributional impacts on not only economic outcomes such as employment (Autor et al. (2013)), but also on socio-economic outcomes. For example, the China shock led to increases in property crime (Beach and Lopresti (2019), Che et al. (2018)). The direct effects can be explained by a well-established relationship between labor markets and crime, whereas the indirect effects include channels such as decreases in public goods provision, deteriorating housing markets, and so on. In this paper, we investigate whether such socio-economic impacts can be found even in the short-run using another large and unexpected trade shock, namely the US-China trade war of 2018-19.

Since January 2018, the U.S. administration under Donald Trump started trade wars along several fronts against U.S. trading partners, most notably with China. As of June 2022, the average rate of U.S. tariffs on Chinese imports is 19.3%, compared to 3.1% in January 2018. China in turn retaliated in full force with average tariffs of 21.2% in June 2022, compared to 8% in January 2018[1].

The short run economic impact of the trade war has been studied by several papers. Flaaen and Pierce (2019) find that U.S. manufacturing industries more exposed to tariff increases experience relative reductions in employment. The positive effect from import protection is offset by larger negative effects from rising input costs and retaliatory tariffs. Like the China shock, the trade war shock also has distributional consequences on economic outcomes.

This paper studies the effect of the trade war shock on socio-economic outcomes at the regional level. Since the linkages between trade shocks and crime outcomes have been established in the past, we start by investigating whether such the recent trade war affects crime even in the short-run and we present evidence that the trade war is indeed associated with a rise in crime rates in counties that were more exposed to the trade war. This effect is more pronounced for property crimes rather than violent crimes. This is consistent with the idea that a large negative employment or income shock generally translates to poorer socioeconomic outcomes.

Our empirical strategy is to exploit the interaction between the introduction of the trade war shock and the pre-trade war characteristics of counties, such as the level of agricultural or manufacturing production. We document that counties that had higher levels of production in the pre-shock period of 2017, exhibit higher levels of crime. The effect is more pronounced for agricultural production than manufacturing production. We show that there are no pre-trends and

[1] Source: Peterson Institute of International Economics - US-China Trade War Tariffs: An Up-to-Date Chart

that this effect is observed after the introduction of the trade war tariffs. Furthermore, we explore outcomes such as farm bankruptcy rates and manufacturing employment to working-age population to show first-order effects.

This paper contributes to the literature on the distributional impacts of trade. Pavcnik (2017) surveys the empirical evidence on the distributional effects of trade in both developed and developing countries. Economists have long recognized that free trade has the potential to raise living standards and that both the importing and exporting countries gain by engaging in trade. The growing body of empirical evidence supports the view of most theoretical trade models that trade reallocates resources within a country, and both destroys and creates jobs, with implications for income distribution. Evidence suggests that while the countries benefit overall, there are some losers as well. Trade's adverse effects appear to be highly geographically concentrated and long-lasting in developing and developed countries alike. The harmful effects of trade are permanent for some workers that lose their jobs to import competition. The "China shock" literature of Autor et al. (2013) and Pierce and Schott (2016) have established that import competition from China contributed to substantial job losses (by around 1.5 million jobs) in U.S. manufacturing in the 1990s and 2000s. In the case of the trade war, this is a shock going in the opposite direction, i.e., tariffs on imports should improve economic outcomes. But Flaaen and Pierce (2019) show that negative effects on employment of Chinese retaliatory tariffs on US exports outweigh small positive effects of US tariffs on Chinese imports. In other words, the trade war also has distributional impacts, and this time those exposed to the retaliatory tariffs by China on US exports are adversely affected. Our paper shows that this adverse impact shows up even for socioeconomic outcomes.

This paper also contributes to another strand of the literature that investigates the effect of trade-induced shocks on socioeconomic outcomes. As Chinese import competition intensified, the resulting decline in labor market conditions led to rising crime, decreased public good provision, increased political polarization, and declining health outcomes. Feler and Senses (2017) analyze trade-induced income shocks and provide evidence related to public goods provision. Pierce and Schott (2020) find evidence that greater import competition led to an increase in "deaths of despair", i.e., drug overdose, suicide, and diseases of the liver in the US. These effects are present primarily among working-age whites. Lang et al. (2019) find adverse effects of import competition on health outcomes, including mental health. McManus and Schaur (2016) show that greater import competition is associated with greater injury rates to workers in factories. Autor et al. (2020) show evidence that greater import competition has led to political polarization in the US.

Lastly, this paper advances a growing literature on the short-run impacts of the US-China trade wars. The key findings are that the trade war led to declines in the both import and export, a complete pass-through of tariffs to consumers and an overall loss in welfare (Fajgelbaum et al. (2020), Amiti et al. (2019)).

The trade war that began in 2018 between the U.S. and its trading partners has distributional consequences across industries, and across regions with different patterns of comparative advantage. Figure 1 shows the exposure to U.S. import tariffs and Chinese tariffs on U.S. exports in December 2018 by regions. Import tariffs seem to be more concentrated in the Rust Belt around the Great Lakes region, whereas retaliatory tariffs seems to be concentrated in the Corn Belt of the Mid-West, which is dominated by farming and agriculture and the North-West part of the country.

Our result indicates that the effect of the trade war as captured by agricultural production did increase crimes in the US even in the short-run. Outlets such as CNBC (Newburger (2019)) reported extensively on how difficult the trade war has been for US farmers. In this paper we provide causal evidence that the trade war indeed has had negative consequences for the US that go beyond economic effects, and shed further light on the unintended consequences of trade policy.

2 Data and Empirical Strategy

Our estimating equation at the monthly level for the period of January 2012 to December 2019 is

$$crime_{ct} = \delta_c + \omega_t + \beta(Post_t \times production_c) + \sum_t \gamma_t \mathbf{1}\{year = t\} \times X_c + \varepsilon_{ct}, \tag{1}$$

where $crime_{ct}$ is the outcome variable of interest in county c in month t. It is defined as the number of crimes, divided by the population of the county times 100,000 residents. δ_c represents a full set of county fixed effects, and ω_t represents a full set of year dummies. X_c is a vector of time-invariant controls at the county level measured at the start of the period. These include demographic controls such as population share by four education levels, gender, four races, seven age bins, as well as economic controls such as the Gini index, median household income, health insurance coverage rate, population share in agriculture, construction, manufacturing, retail, and finance sectors. Since these do not vary over time, we include specifications with and without these controls, with and without county fixed effects, as well as a specification where we have county fixed effects in addition to county controls interacted by year dummies. Regressions are weighted by the population of the county in 2012, and standard errors are clustered at the county level.

$Post_t$ is a dummy variable that equals one for the post-trade war period, i.e., January 2018 onwards. $production_c$ is log agricultural production for each county in the pre-treatment period of

2017, or log trade war affected manufacturing production for each county in 2016[2]. Since production is likely to respond endogenously to the trade war, we measure these variables in 2016 or 2017, prior to the start of the trade war. The identifying assumption in estimating equation (1) is that, without the trade war shock, counties with different $production_c$ would not have experienced differential changes in their outcomes in the post-trade war period. The main variable of interest is the interaction term $Post_t \times production_c$ with coefficient β.

We further investigate whether there are any differential trends in the outcome variables by the level of production in any of the pre-trade war years. For this purpose we re-estimate equation (1) at the yearly level and also estimate a more flexible version of this equation as follows:

$$crime_{ct} = \delta_c + \omega_t + \sum_{t>2012} \beta_t (d_t \times production_c) + \sum_t \gamma_t \mathbf{1}\{year = t\} \times X_c + \varepsilon_{ct}, \tag{2}$$

One important control variable we consider is the shares of votes to the Republican party in the 2016 election in each county. If there is reason to believe that China might have targeted Trump counties on purpose as a retaliation to Trump's tariffs, and that these counties are usually those that have higher crimes rates, then this variable can help control for this. Election data comes from David Leip's Atlas of US Presidential Elections.

Data on agricultural production comes from the 2017 Census of Agriculture, collected by National Agricultural Statistics Service (NASS). For each county in the United States, there is information on the market value of agricultural products sold, as well as a breakdown by crops such as corn, wheat, soybeans, etc. For our measure of agricultural production, we use the dollar value of agricultural commodities sold for each county in 2017. Since bulk of the tariffs imposed by China were on US agricultural exports, we can consider any effects on agricultural production to be representing the effect of Chinese retaliation in the trade war.

Data on manufacturing production comes from the 2016 Annual Survey of Manufacturers (ASM) of the U.S. Census Bureau. This is available at the 6-digit North American Industry Classification System (NAICS) level. In order to have a county-level measure of industrial production, employment is used as weights in the following manner:

$$production_c = \sum_{j \in J} \frac{L_{c,j,2016}}{L_{c,2016}} production_j,$$

where $production_c$ is manufacturing production in 2016 at the county level and $production_j$ is manufacturing production in 2016 at the industry level. $L_{c,j,2016}$ is the employment level in 2016 at

[2]The Annual Survey of Manufactures (ASM) collects information for all years except those ending in 2 and 7. Since, we do not have this information for the pre-treatment year or 2017, we instead use the 2016 ASM.

the county-industry level, whereas $L_{c,2016}$ is the employment level in 2016 at the county level. Data on employment is from the Quarterly Census of Employment and Wages (QCEW) of the Bureau of Labor Statistics (BLS). Employment data is available at the 6-digit NAICS industry-county level.

Not all manufacturing industries were impacted by the tariff increases in 2018-19. The treatment variable in the case of manufacturing production is therefore constructed by matching the production in 6-digit NAICS industries with the corresponding tariff change that occurred post-2018. More specifically, we take data on tariffs imposed by US and China from Bown (2021) at Harmonized System (HS) 10 and 8 digit respectively. We compute the difference between tariffs in January 2018 (before the trade war) and December 2018 (after the bulk of the trade war activity). We tranform this information to the 6-digit NAICS level using total US trade, i.e., sum of imports and exports, as weights. If this trade-weighted average tariff is positive for a certain 6-digit industry, then we define that industry as an affected industry. The treatment variable therefore take three forms - manufacturing production affected by both US and Chinese tariffs, manufacturing production affected by only US tariffs, and manufacturing production affected by only Chinese tariffs. Then we apply the shift-share transformation described above to obtain county level trade war-affected manufacturing production.

The outcome variable is defined as the number of crimes in Federal Bureau of Investigation (FBI) National Incident-Based Reporting System (NIBRS), divided by the population of the county times 100,000 residents. The crime data from NIBRS is available at the reporting agency level and we use crosswalks between Originating Agency Identifier (ORI) code to county Federal Information Processing Standard (FIPS) codes from the US Bureau of Justice Statistics (BJS) to transform this information. These crimes are then categorized into two main offenses as per BJS's usual definition. Property offenses include burglary, arson, larceny, theft, pocket picking, purse snatching, and shoplifting, whereas violent offenses include assault, rape, murder and robbery. The crime variables are divided by the county's population $\times$ 100,000 residents. Data on population at the county level is obtained from the US Census Bureau.

In order to establish first-order effects, we also include a few more outcome variables. The first is Chapter 12 farm bankruptcy. Chapter 12 was enacted in 1986 as a response to the 1980s farm crisis and it went into effect on November 26, 1986. Data on individual filings from 2008 is extracted from Robert Dinterman's respository[3]. From this we construct a measure of farm bankruptcy at the monthly level, and divide it by the population of the county $\times$ 100,000 residents. If the effect of the trade war on crime is coming via the channel of economic distress, then the

[3]https://www.robertdinterman.com/historical-bankruptcies/

first-order effect can be captured by the number of farm bankruptcy filings in the case where the treatment is agricultural production.

When the treatment is manufacturing production, we rely on manufacturing employment to check for first-order effects. Data on employment is from the Quarterly Census of Employment and Wages (QCEW) of the Bureau of Labor Statistics (BLS). Employment data is available at the monthly county level. We then construct the rate of employment by dividing manufacturing employment by the working age population in the county. Working age population at the county level is constructed from population for different age groups as obtained from the US Census Bureau.

Finally, county-level time-invariant controls are obtained from 5-year American Community Survey (ACS) summary files of 2008-2012. The data is available on Integrated Public Use Microdata Series (IPUMS) National Historical Geographic Information System (NHGIS). We control for demographic characteristics such as population share by four education levels, gender, races, several age bins, health insurance coverage. We also control for economic characteristics such as labor force participation rate, inequality index and median housing costs.

Summary statistics of all relevant variables are provided in Tables 1 and A.1.

3 Results and Concluding Remarks

Table 2 shows our results from estimating (1) where in Panel I, $production_c$ is log agricultural production by each county in 2017, with the first two columns representing two types of crimes, and the third column represents farm bankruptcy rates. We run four variations of this equation. Specification A does not include county fixed effects or time invariant county controls. Specification B includes county fixed effects. Specification C removes county fixed effects and instead includes all of the county controls mentioned above. Specification D includes both county fixed effects as well as county controls that are interacted with year dummies. The evidence suggests that counties that had higher levels of agricultural production in the pre-shock period of 2017, exhibit higher levels of crimes in the post-shock period. This result is statistically significant. The result for property crimes is more pronounced than for violent crimes, and this is consistent with the idea that a negative economic shock prompts people to commit property-related crimes, rather than violent crimes.

Panel II is identical but instead shows our results from estimating (1) where $production_c$ is log affected industrial production by each county in 2016. These results have much smaller coefficients than those in Panel A. For our most robust specification D, we find that there is no impact on

Table 1: Summary Statistics by county

	Obs	Mean	Std. Dev.
I. Production			
Agricultural production (in $ 1000)	81432	123000	179000
Industrial production (in $1000)	81432	784042.7	2150000
Log of agricultural production	81432	17.8	1.552
Log of industrial production	38591	13.37	1.481
II. Employment			
Total employment	81432	33537.11	112000
Goods producing employment	81432	6527.12	17969.59
Agricultural employment	81432	161.87	994.99
Log of total employment	81055	8.92	1.61
Log of goods producing employment	80874	7.56	1.57
Log of agricultural employment	49156	4.23	1.39
III. Crime			
Property offenses	81432	109.9	360.28
Violent offenses	81432	16.6	70.28
Drug offenses	81432	42.26	108.06
Non-violent offenses	81432	163.15	483.37
Property offenses by population *times* 100,000 residents	81432	51.24	43.26
Violent offenses by population *times* 100,000 residents	81432	7.28	8.11
Drug offenses by population *times* 100,000 residents	81432	30.99	54.73
Non-violent offenses by population *times* 100,000 residents	81432	87.28	80.49
III. Population			
Total population in 2016	81432	175670.47	485000
Working-age population in 2016	81432	57722.34	162000

Table 2: The impact of the 2018-19 trade war on crime rates, farm bankruptcy and manufacturing employment by working-age population (monthly estimation: 2012-2019)

I. Post × log agricultural production	**Property Offense** (1)	**Violent Offense** (2)	**Farm Bankruptcy** (3)
A. No county controls and no county fixed effects	0.67***	0.07***	0.0064***
	(0.13)	(0.02)	(0.00)
B. County fixed effects	0.63**	0.07	0.0005***
	(0.32)	(0.06)	(0.00)
C. Time-invariant county controls	0.68***	0.08***	0.0039***
	(0.13)	(0.02)	(0.00)
D. County fixed effects and year-interacted county controls	0.46***	0.09***	0.0002
	(0.16)	(0.03)	(0.00)
II. Post × log affected manufacturing production	**Property Offense** (1)	**Violent Offense** (2)	**Manufacturing Employment** (3)
A. No county controls and no county fixed effects	0.21***	0.03***	-0.32
	(0.07)	(0.01)	(2.50)
B. County fixed effects	1.17***	0.16**	1.46
	(0.33)	(0.07)	(3.76)
C. Time-invariant county controls	0.21***	0.03***	-0.39
	(0.07)	(0.01)	(2.50)
D. County fixed effects and year-interacted county controls	0.20**	0.02	-6.85**
	(0.08)	(0.01)	(3.39)

Notes: Robust standard errors in parentheses, clustered at the county level. The estimations comes from specification (1). In Panel I, $production_c$ is log agricultural production by each county in 2017 and in Panel II, $production_c$ is log trade war-affected manufacturing production by each county in 2016. There are approximately 2,500 counties and the data for crime is at the monthly level from January 2012 to December 2019. The regressions are weighted by the population of each county in 2012. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

violent crimes.

Tables 3 and 4 show results from estimating (2). We see that there are no pre-trends for property crime.

These results are in line with Flaaen and Pierce (2019)'s paper where they find that U.S. industries more exposed to tariff increases experience relative reductions in employment, as a small positive effect from import protection is offset by larger negative effects from rising input costs and retaliatory tariffs. Moreover, they find that counties more exposed to rising tariffs exhibit relative increases in unemployment rates. Therefore, the immediate impacts of the trade war were such that US tariffs on Chinese imports did not reap much benefits, but the Chinese retaliatory tariffs on US exports led to a decline in employment, or a rise in unemployment. These impacts then

Table 3: The impact of the 2018-19 trade war on crime rates (annual estimation: 2012-2019)

	Property Offense		**Violent Offense**	
	(1)	(2)	(3)	(4)
$Post \times production_c$	5.71***		1.09***	
	(2.08)		(0.37)	
$d_{2013} \times production_c$		1.87		-0.90**
		(2.30)		(0.39)
$d_{2014} \times production_c$		-0.75		-0.70
		(2.59)		(0.47)
$d_{2015} \times production_c$		-3.00		-0.40
		(2.92)		(0.48)
$d_{2016} \times production_c$		2.51		-0.87*
		(2.70)		(0.50)
$d_{2017} \times production_c$		3.97		-0.16
		(3.65)		(0.51)
$d_{2018} \times production_c$		5.89*		0.28
		(3.58)		(0.48)
$d_{2019} \times production_c$		7.13**		0.95*
		(3.56)		(0.57)

Notes: Robust standard errors in parentheses, clustered at the county level. The estimations comes from specification (2), where $production_c$ is log agricultural production by each county in 2017. There are approximately 2,500 counties and the data for crime is at the annual level from 2012 to 2019. The regressions are weighted by the population of each county in 2012. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

Table 4: The impact of the 2018-19 trade war on crime rates

	Property Offense		**Violent Offense**	
	(1)	(2)	(3)	(4)
$Post \times production_c$	2.16*		0.16	
	(1.11)		(0.16)	
$d_{2013} \times production_c$		1.21		-0.03
		(1.04)		(0.16)
$d_{2014} \times production_c$		0.93		0.09
		(1.33)		(0.19)
$d_{2015} \times production_c$		1.43		-0.10
		(1.45)		(0.21)
$d_{2016} \times production_c$		1.77		-0.25
		(1.53)		(0.21)
$d_{2017} \times production_c$		1.26		-0.11
		(1.64)		(0.22)
$d_{2018} \times production_c$		3.37*		0.01
		(1.74)		(0.24)
$d_{2019} \times production_c$		2.37		0.05
		(1.87)		(0.25)

Notes: Robust standard errors in parentheses, clustered at the county level. The estimations comes from specification (2), where $production_c$ is log trade war-affected manufacturing production by each county in 2016. There are approximately 2,500 counties and the data for crime is at the annual level from 2012 to 2019. The regressions are weighted by the population of each county in 2012. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

translate to poorer socioeconomic outcomes as well. In this paper, we show that crime rates are adversely impacted due to the 2018-19 US-China trade war.

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Table A.1: Summary Statistics of control variables by county

	Obs	Mean	Std. Dev.
Median housing cost	81414	33.2	19.895
Proportion of white males	81432	0.5	0.02
Proportion of white females	81432	0.5	0.02
Proportion of males in the labor force	81432	0.98	0.41
Proportion of females in the labor force	81432	0.93	0.41
Proportion of individuals with less than high school education	81432	0.11	0.06
Proportion of individuals with high school education	81432	0.34	0.08
Proportion of individuals with college education	81432	0.33	0.06
Proportion of individual with education higher than a college degree	81432	0.22	0.10
Proportion of male health coverage	81432	0.5	0.01
Proportion of female health coverage	81432	0.5	0.01
Male age group: 15-17	77744	0.05	0.10
Male age group: 18-19	77744	0.05	0.09
Male age group: 20-24	77744	0.11	0.14
Male age group: 25-29	77744	0.08	0.11
Male age group: 30-34	77744	0.08	0.11
Male age group: 35-44	77744	0.14	0.14
Female age group: 15-17	74693	0.05	0.10
Female age group: 18-19	74693	0.05	0.10
Female age group: 20-24	74693	0.1	0.16
Female age group: 25-29	74693	0.07	0.12
Female age group: 30-34	74693	0.06	0.11
Female age group: 35-44	74693	0.11	0.14

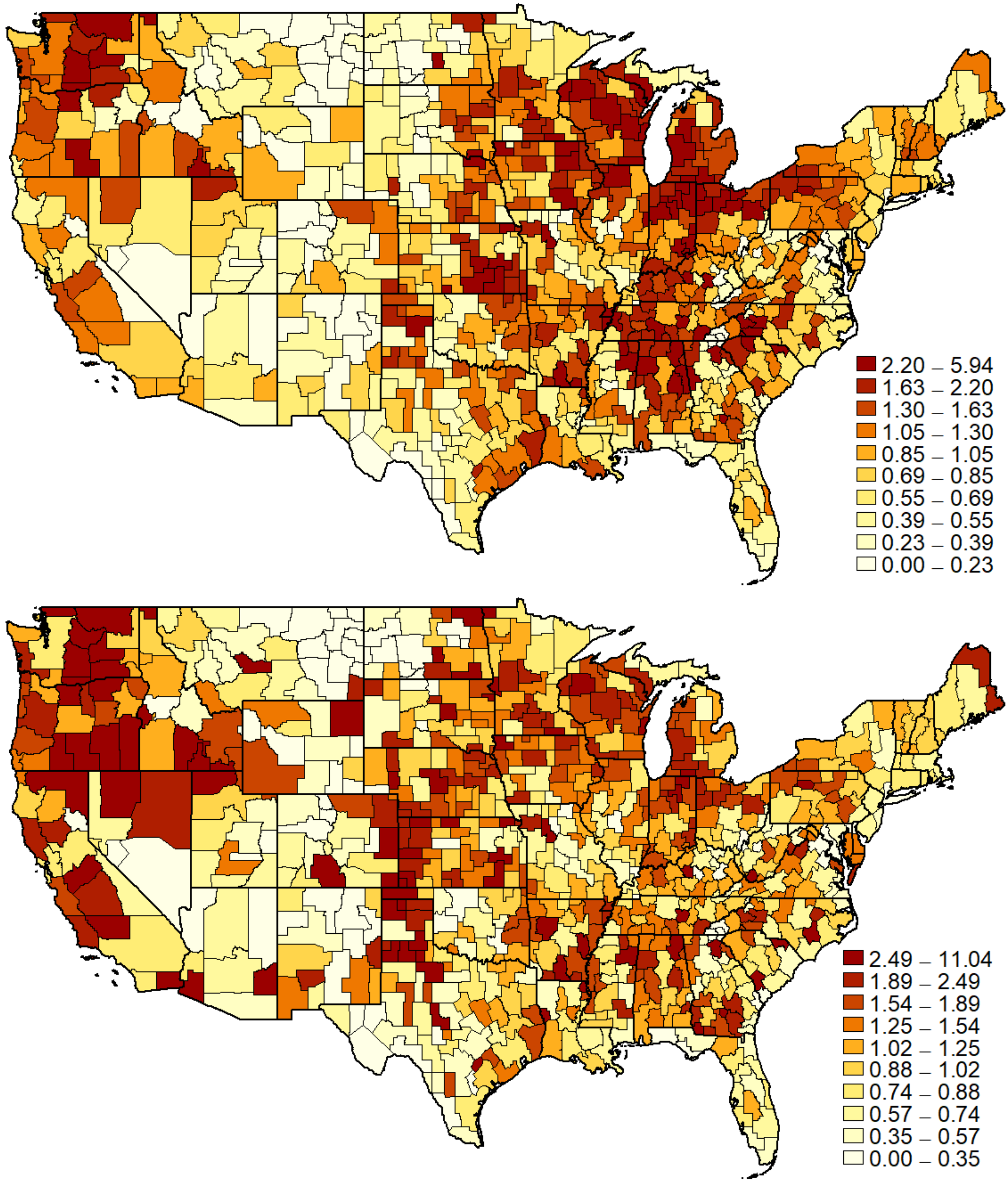

Figure 1: U.S. import tariffs (top) and Chinese retaliatory tariffs on U.S. exports (bottom) in December 2018 by region