U.S. Trade War and Socioeconomic Outcomes*

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Abstract

We investigate 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 and non-violent 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.

JEL Classification: F13, F14

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 and non-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 and production. We document that counties that had higher levels of agricultural production in the pre-shock period of 2016, exhibit higher levels of crime.

This paper contributes to the literature on the distributional impacts of trade. Pavcnik (2017)

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

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.

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)). Flaaen and Pierce (2019) find that the negative effects on employment of Chinese retaliatory tariffs on US exports outweigh small positive effects of US tariffs on Chinese imports.

The trade war that began in 2018 between the U.S. and its trading partners also 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 indicate that the effect of the trade war as captured by the manufacturing industry did not affect crimes but the effect of the trade war as captured by the agriculture 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 and we can even observe trade-induced crime increases.

2 Data and Empirical Strategy

The impact of the trade war on crime should be larger for counties with a higher pre-trade war amount of production. On the basis of this reasoning, our basic estimating equation is as follows:

$$crime_{ct} = \beta_c + \beta_t + \eta X_{ct} + \beta(Post_t \times prewar_c) + \varepsilon_{ct}, \tag{1}$$

where c = county, t = month (2016 m1 to 2019 m12) or quarter (2016 q1 to 2019 q4), X_{ct} consists of control variables which are not added in the baseline regressions but will be added in robustness checks, $Post_t$ is a dummy variable that equals one for the post-trade war period, i.e., January 2018 onwards. β_c represents a full set of county fixed effects, and β_t represents a full set of year dummies. Standard errors are clustered at the county level. Regressions are weighted by the population of the county in 2016.

$prewar_c$ is (a) log agricultural production for each county in 2017, and (b) log industrial production for each county in 2016. 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 $prewar_c$ would not have experienced differential changes in their outcomes in the post-trade war period.

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 industrial 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:

$$prewar_c = \sum_{j \in J} \frac{L_{c,j,2016}}{L_{c,2016}} prewar_j,$$

where $prewar_c$ is industrial production in 2016 at the county level and $prewar_j$ is industrial production in 2016 at the industry level. $L_{c,j,2016}$ is the employment level in 2016 at 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.

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 four main offenses as per BJS's usual definition. Property offenses include burglary, arson, larceny, theft, pocket picking, purse snatching, and shoplifting. Violent offenses include assault, rape, murder and robbery. Drug offenses include drug violations and drug equipment violations. Non-violent offenses include property offenses, drug offenses, and a few other offenses such as credit card or atm fraud, wire fraud, welfare fraud, and weapon law violations. 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.

Finally, county-level time-invariant controls are obtained from 5-year American Community Survey (ACS) summary files 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 and median housing costs.

The main variable of interest is the interaction term $Post_t \times prewar_c$ with coefficient β. Summary statistics of all relevant variables are provided in Tables 1 and A.1.

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

I. Post × log agricultural production	Property Offense (1)	Violent Offense (2)	Drug Offense (3)	Non-violent Offense (4)
A. No county controls and no county fixed effects	0.76***	0.18***	0.40	1.20***
	(0.22)	(0.05)	(0.24)	(0.39)
B. County fixed effects	0.76***	0.18***	0.41*	1.22***
	(0.23)	(0.05)	(0.25)	(0.40)
C. Time-invariant county controls	0.79***	0.16***	0.32	1.14***
	(0.24)	(0.05)	(0.26)	(0.43)
D. County fixed effects and year-interacted county controls	0.96***	0.12**	0.29	1.25***
	(0.26)	(0.05)	(0.28)	(0.46)
II. Post × log industrial production	Property Offense (1)	Violent Offense (2)	Drug Offense (3)	Non-violent Offense (4)
A. No county controls and no county fixed effects	0.40	-0.06	-0.08	0.33
	(0.37)	(0.06)	(0.20)	(0.49)
B. County fixed effects	0.43	-0.06	-0.08	0.36
	(0.38)	(0.07)	(0.20)	(0.51)
C. Time-invariant county controls	0.40	-0.04	-0.04	0.37
	(0.37)	(0.06)	(0.20)	(0.50)
D. County fixed effects and year-interacted county controls	0.54	-0.02	-0.03	0.53
	(0.39)	(0.07)	(0.20)	(0.52)

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

3 Results and Concluding Remarks

Table 2 shows our results from estimating (1) where in Panel I, $prewar_c$ is log agricultural production by each county in 2017, with each column representing a type of crime. 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 2016, exhibit higher levels of crimes. This result is statistically significant.

Panel II is identical but instead shows our results from estimating (1) where $prewar_c$ is log industrial production by each county in 2016. The results are vastly different. There does not seem to be any statistically significant relationship. In other words, counties that had higher levels of industrial production before the trade war do not seem to be differentially impacted by the trade war.

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. The lack of a relationship between greater pre-trade war levels of industrial production and crime can be explained by this non-responsiveness of US import tariffs in the short-run, whereas the robust relationship between greater pre-trade war levels of agricultural production and crime can be explained by the significant responsiveness of Chinese retaliatory tariffs on US exports.

4 Work in Progress

We plan to estimate a more flexible version of equation (1) as follows:

$$crime_{ct} = \beta_c + \beta_t + \eta X_{ct} + \sum_{t \geq 2016} \beta_t (d_t \times prewar_c) + \varepsilon_{ct}, \tag{2}$$

where β_t provides a separate coefficient for the year 2016 and each subsequent year, and d_t is an indicator variable for year t. This model allows both time-varying post-trade war effects and also a more flexible investigation of whether there are any differential trends in the variables of interest in any of the pre-trade war years.

We also plan to investigate effects on other socioeconomic outcomes.

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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

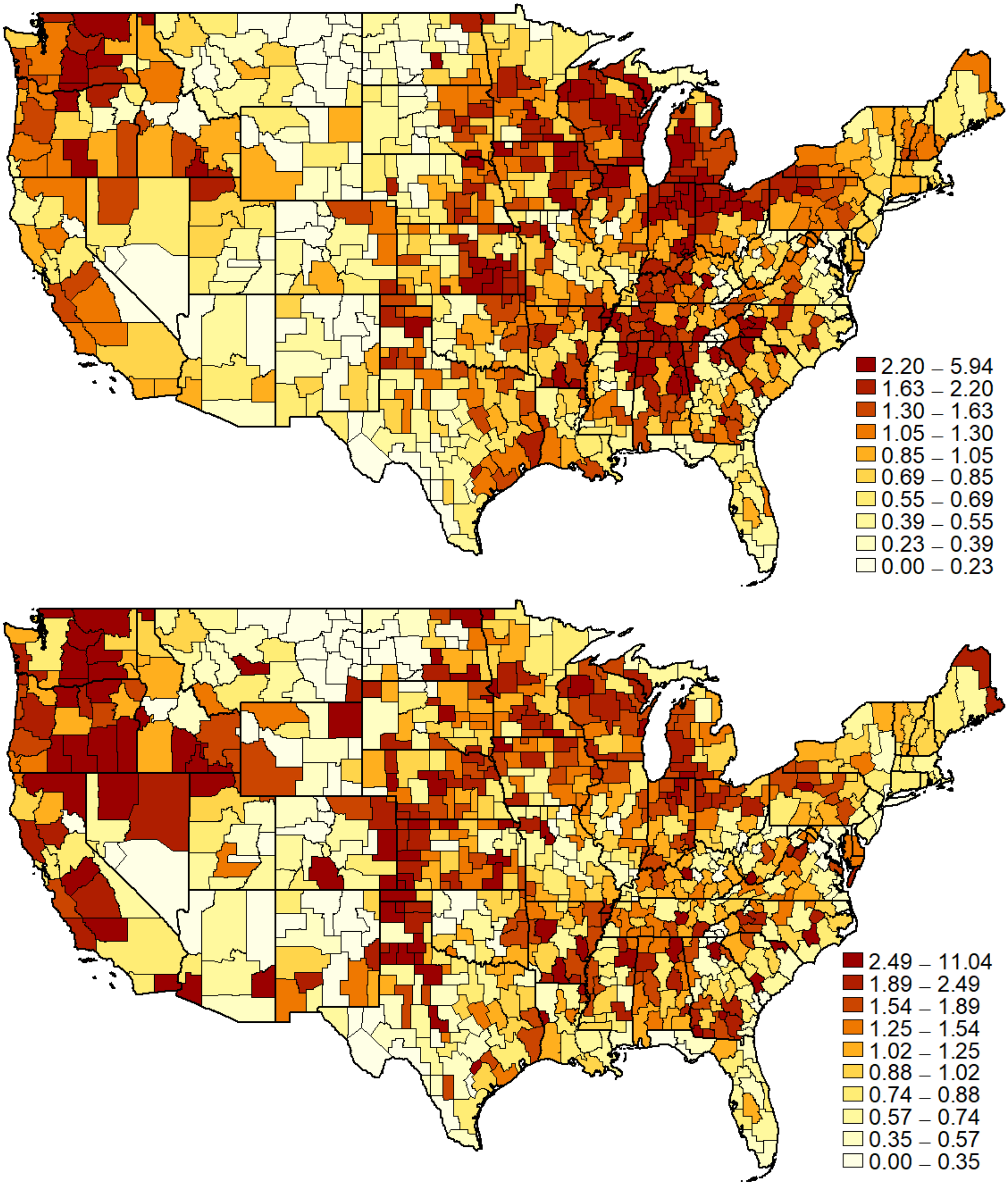

Figure 1: U.S. import tariffs (top) and Chinese retaliatory tariffs on U.S. exports (bottom) in December 2018 by region