The Consumption Response to Trade Shocks

Evidence from the US-China Trade War

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What are the distributional impacts of trade shocks?

The "model" in everyone's head (my mom, President Trump, Lyon and Waugh (2019))...

$$\text{trade} \Rightarrow \text{labor market outcomes} \Rightarrow \text{consumption} \Rightarrow \text{welfare}$$

My paper does two things:

1. Measure how trade-induced changes in labor market opportunities affect consumption.
   - We know something about the first arrow (e.g., Autor, Dorn, and Hanson (2013)).
   - We know nothing about the second.

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- We know nothing about the second.
- Why not? (I) Separating trade from other stuff is hard.

  Via comparative advantage, technology and trade are intertwined—hard to tell them apart.

  US-China Trade War $\Rightarrow$ a unique setting with a policy induced change in trade.

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1. Measure how trade-induced changes in labor market opportunities affect consumption.

- We know something about the first arrow (e.g., Autor, Dorn, and Hanson (2013)).
- We know nothing about the second.
- Why not? (II) Measuring consumption is hard.

  So I'm going to proxy consumption with the universe of new auto sales at monthly frequency, county level. And correlate it with policy actions in the US-China Trade War.

What are the distributional impacts of trade shocks?

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My paper does two things:

2. Evaluate the economic consequences of the US-China trade war.

- Distributional outcomes are at the heart of Trump’s trade policy (at least rhetorically).
  So you cant’t evaluate **2.** without answering **1.**
- Did US tariffs on Chinese imports benefit workers (in labor market opportunities & consumption)?
- Did Chinese retaliation harm US workers?

What are the distributional impacts of trade shocks?

The "model" in everyone's head (my mom, President Trump, Lyon and Waugh (2019))...

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My paper does two things:

2. Evaluate the economic consequences of the US-China trade war.

- Distributional outcomes are at the heart of Trump's trade policy (at least rhetorically). So you cant't evaluate **2.** without answering **1.**
- Did US tariffs on Chinese imports benefit workers (in labor market opportunities & consumption)? **No** evidence that US tariffs increased employment or consumption.
- Did Chinese retaliation harm US workers? **Yes.** Employment $\searrow$. Auto sales growth $\searrow$ by ≈ 4 p.p. in high-tariff counties relative to low-tariff counties $\Rightarrow$ up to $845 fall in consumption per person.

What I am NOT doing. . .

The "model" in the trade literature's head...

trade $\Rightarrow$ prices of goods / variety $\Rightarrow$ consumption $\Rightarrow$ welfare

For example, how US tariffs on Chinese goods lowered imports and increased prices, Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019), Amiti, Redding, and Weinstein (2019), Cavallo, Gopinath, Neiman, and Tang (2019)

This is an important channel, but well understood, explored extensively beyond the trade war.
See, e.g., Costinot and Rodríguez-Clare (2018)

My paper is distinctly different and about a conceptually important, but unknown channel.

How trade and tariffs feed into consumption through changes in labor income/production opportunities.

Tariff Data and County Exposure

US tariff data from USTR and Federal Registrar. Chinese tariffs from Bown, Jung, and Zhang (2019).

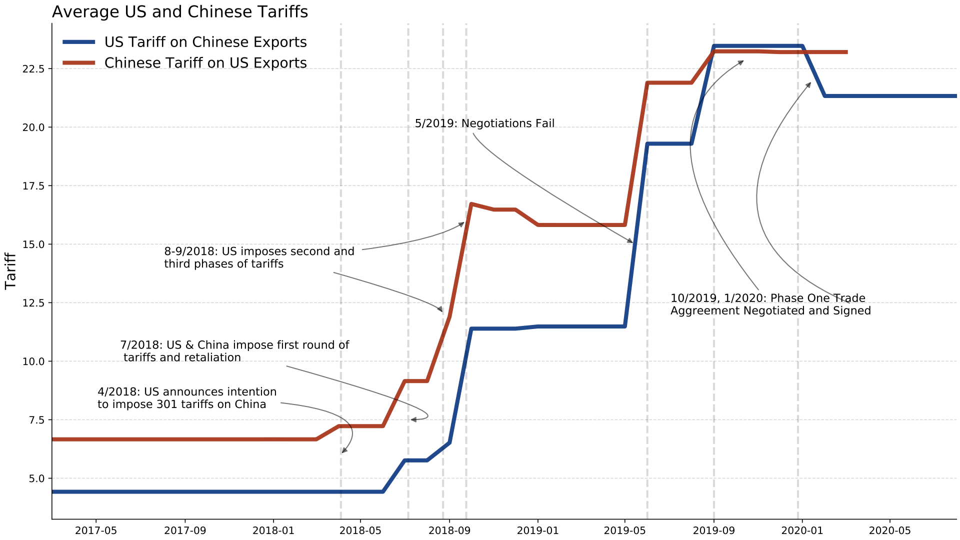
- At HS10 level and then mapped into three-digit NAICS.
- Start from MFN rates in 2017, measure tariff changes onward.

My measure of tariff exposure at the county level:

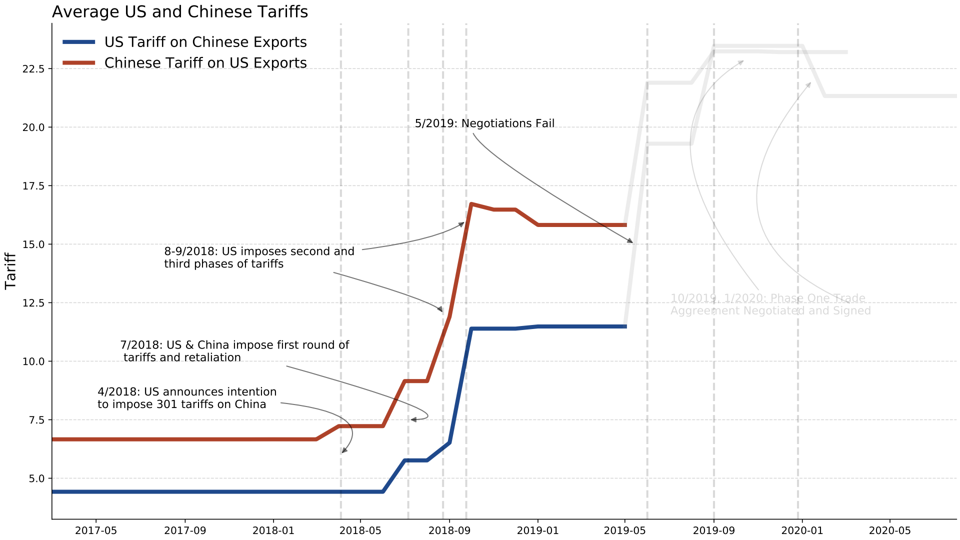
$$\tau^i_{c,t} = \sum_{s \in S} \frac{L_{c,s,2017}}{L_{c,S,2017}} \ \tau^i_{s,t},$$

- $\frac{L_{c,s,2017}}{L_{c,S,2017}} =$ 2017 share of county c's employment in industry s.
- $\tau^i_{s,t}$ is the implemented tariff by country i, industry s, date t.
- Idea: if a county's employment is all in soybeans, then the county is protected and/or faces the soybean tariff.

Trade War! Average US and Chinese Tariffs



Trade War! Average US and Chinese Tariffs, My Paper's Focus



Tariff Exposure by County, NAICS Industry, and Time

See the graphics at my site `www.tradewartracker.com`

- US tariff on Chinese products by geography and industry
- Chinese tariffs on US products by geography and industry

My Consumption Measure: New Auto Sales

From IHS Polk. Counts of new auto sales (not values).

- At the county level (by local of registration, not sale),
- Monthly from January 2016 to August 2020 (I have an ongoing licence),
- By make (e.g. Ford) and model (F-150).

Derived from registration data from State DMVs.

While just autos, a very compelling, high-quality measure...

- Essentially an "administrative" level dataset. In levels it matches NIPA very closely.
- High-frequency, detailed geographic variation, near real time. Can't be matched by CEX or PSID.
- Not subject to sampling or provider issues as in other propriety datasets (e.g Kilts-Nielsen, Credit/Debit card transactions data).

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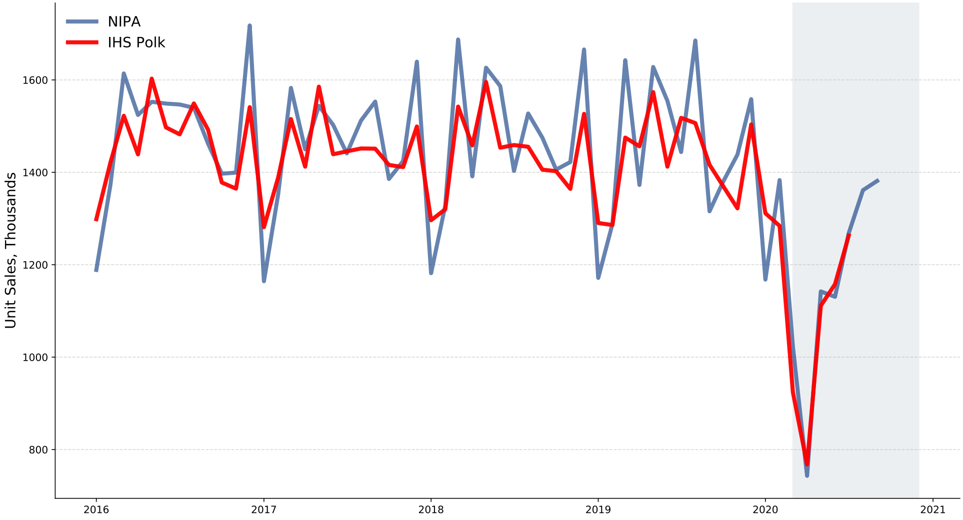
Derived from registration data from State DMVs.

Today: Just going to focus on

- only lightweight vehicles, e.g. busses/ semi-trucks are dropped.
- aggregate at the county level; won't exploit make/model variation.

Aggregate Auto Sales: IHS vs NIPA



Employment Data

The want operator:

How changes in tariff exposure affect labor market outcomes and consumption.

Employment data from BLS's Quarterly Census of Employment and Wages.

At the county level. Focus on two measures of private sector employment.

- Total employment,
- Good-producing employment (natural resources, manufacturing, and construction).

Market Facilitation Payments (MFP)

Trump Administration and USDA set up the Market Facilitation Program to assist farmers "directly impacted by unjustified foreign retaliatory tariffs" (from the website).

- 2018 program paid out direct $$$ based upon crop harvested.
- Trump Administration authorized up to $12 billion USD; in my data $8.6 billion was paid out.

This is public record.

So I applied through the Freedom of Information Act (FOIA) and asked for all payments, who received them, and the addresses to which the payments were made.

- The address are a unique, novel part of my data.
- I have a measure of the location of where the payment was received, not the location of production.

Summary Statistics (Sorted on China Tariff)

Summary Statistics: Tariffs, Autos, Trade, Employment (Sorted on China Tariff)

Δ Tariff Quartile	Δ China Tariff	Δ US Tariff	Autos	Total Emp.	Goods Emp.	Population	MFP per person
Upper quartile	3.80	2.02	1,359	10,379	6,359	35,115	95.0
25th-75th quartiles	0.98	0.92	7,977	53,049	8,978	140,085	21.0
Bottom quartile	0.10	0.36	4,688	33,667	1,765	82,627	14.7
Average	1.46	1.05	5,524	37,536	6,521	99,478	26.2
Number of Counties	3,122						

Note: All values are for the year 2017; Δ Tariff is the change in the tariff between end of March 2017 and end of April 2019. Population and Income are from the American Community Survey.

Research Design

Step 1: Time aggregate levels at the bimonthly level. Then focus on year over year log differences.

- Minimizes year over year variation induced by changes in weekend effects, holiday position, etc.

Step 2: Explore different permutations of the following specification:

$$\Delta \log Y_{c,t} = \sum_{i \in \{ch, us\}} \beta_i \Delta \log(1 + \tau^{i}_{c,t}) + \sum_{y=B1,2017}^{B2,2019} \left(1\{t = y\} X_c^{'} \delta_y\right) + X_{c,t}^{'} \lambda + \alpha_t + \alpha_0 + \epsilon_{c,t}$$

- β_is are the coefficient of interest, answers how the change in the tariff affected employment and consumption.
- δ_ys are the coefficients on interactions of fixed, county-level characteristics with time. Hope is to control for (i) pre-trends and (ii) other $c \times t$ shocks during the treatment period.
- λ are coefficients on time varying county-level characteristics; mostly just receipt of Market Facilitation Program payments.
- Standard errors are clustered at the county level. Observations weighted by 2017 population.

Research Design

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Identification and Interpretation (I)

- If you want a causal statement, then assume the error term $\epsilon_{c,t}$ satisfies a "parallel trends" assumption.
- Structural interpretation of this assumption:
  - Lyon and Waugh (2019) model links local outcomes with changes in trade or tariffs.
  - In this context, the requirement is that tariffs are uncorrelated with the change in the local productivity shock.

Research Design

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Interpretation (II)

- When consumption is on the LHS, this is essentially same as in Townsend (1994); Cochrane (1991); Mian et al. (2013).
- Interpretation—with complete markets/full risk sharing, there tariff should not pass-through to consumption growth.

Research Design

Step 3: Explore how the tariff effects vary across time:

$$\Delta \log Y_{c,t} = \sum_{i \in \{ch,us\}} \sum_{y=B1,2017}^{B2,2019} \left(1\{t = y\}\, \beta_{i,y} \Delta \log(1 + \tau^{i}_{c,B2,2019}) \right)$$

$$+ \sum_{y=B1,2017}^{B2,2019} \left(1\{t = y\}\, X_c^{'} \delta_y \right) + X_{c,t}^{'} \lambda + \alpha_t + \alpha_0 + \epsilon_{c,t}$$

- Idea: Fix the tariff to it's value in 2019 and estimate the future tariffs effect for each time period.
- Should reveal any anticipation effects and/or pre-existing trend issues.

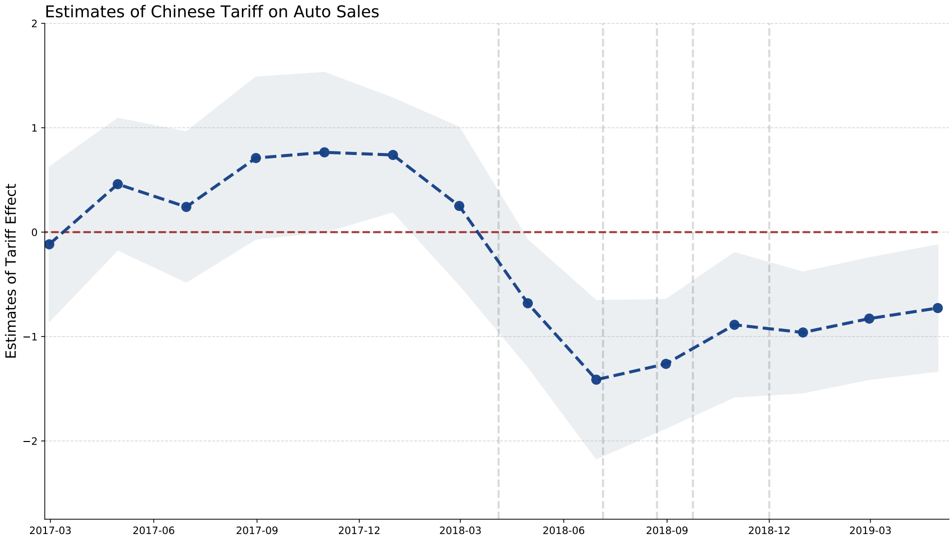
Chinese Retaliatory Tariffs Reduced Auto Sales; US Tariffs Nothing

Auto Sales Growth and Tariff Exposure

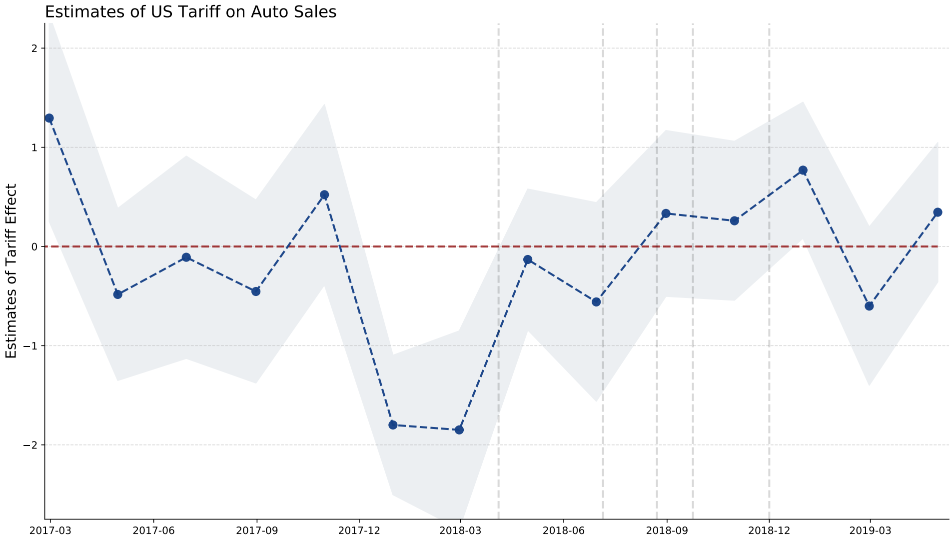
	(1)	(2)	(3)	(4)	(5)
China $\Delta \log(1+\tau_{c,t})$	**-0.95***** [0.20]		**-0.86***** [0.18]	**-1.12***** [0.21]	**-1.00***** [0.22]
US $\Delta \log(1+\tau_{c,t})$		**-0.84***** [0.25]	**-0.12** [0.65]	**0.00** [0.31]	**0.25** [0.31]
$\Delta \log MFP_{c,t}$				**-0.00** [0.00]	**-0.00** [0.00]
Time Effects	N	N	N	Y	Y
Time $\times$ Observables Controls	N	N	N	N	Y
# Observations	43,480				
Time Period	Jan/Feb 2017 - March/April 2019				

Note: Dependent variable is 12 month, log differenced auto sales. County-level observations are weighted by a county's 2010 population. Standard errors are clustered at the county level and are reported in brackets.

Effect of Chinese Tariffs by Time on Auto Sales



Effect of US Tariffs by Time on Auto Sales



Summary of Consumption Results

1. Strong evidence that Chinese retaliation is passing through to consumption.

- Across all specifications, the point estimates are negative, significant, and same size.
- Interpretation: Move from bottom to top quartile of the tariff distribution $1.0 \times (3.80 - 0.10) = 3.7$ percentage point **decrease** in consumption growth.

2. No evidence that US tariffs increased consumption.

- Point estimates vary widely and not statistically significant. Magnitude, in the most optimistic case, is 1/5 the effect of Chinese tariffs.
- With that said, that there still appears to be a negative pre-trend on US tariff side. Consistent with the idea that US tariff list was selected to benefit declining US industries.

3. No evidence that the MFP program helped.

- Point estimates always around zero. Summary statistics and casual observation: MFP looks like corporate giveaway and graft.

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Next Step: Employment

Remember the want: Explore how changes in tariff exposure labor market outcomes and consumption.

Same exact analysis but employment measures on the LHS.

Chinese and US (!) Tariffs Reduced Employment

Total Employment Growth and Tariff Exposure

	(1)	(2)	(3)	(4)
China $\Delta \log(1+\tau_{c,t})$	**-0.30***** [0.06]		**-0.25***** [0.06]	**-0.22***** [0.06]
US $\Delta \log(1+\tau_{c,t})$		**-0.35***** [0.09]	**-0.28***** [0.09]	**-0.25***** [0.09]
$\Delta \log MFP_{c,t}$				**-0.003***** [0.00]
Time Effects	Y	Y	Y	Y
Time $\times$ Observables Controls	Y	Y	Y	Y
# Observations	43,480			
Time Period	Jan/Feb 2017 - March/April 2019			

Note: Dependent variable is 12 month, log differenced employment. County-level observations are weighted by a county's 2010 population. Standard errors are clustered at the county level and are reported in brackets.

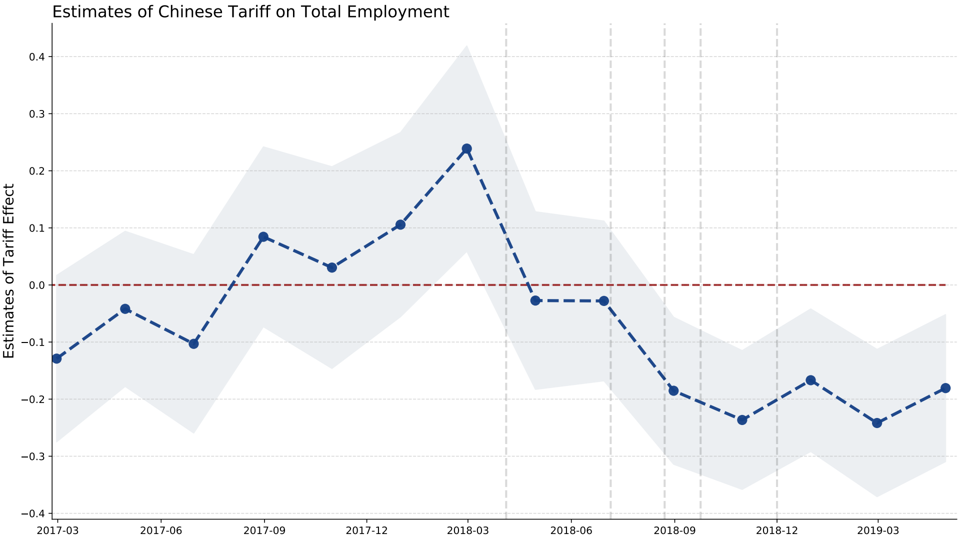
Chinese Tariffs Reduced Goods Producing Employment, US (?)

Goods Employment Growth and Tariff Exposure

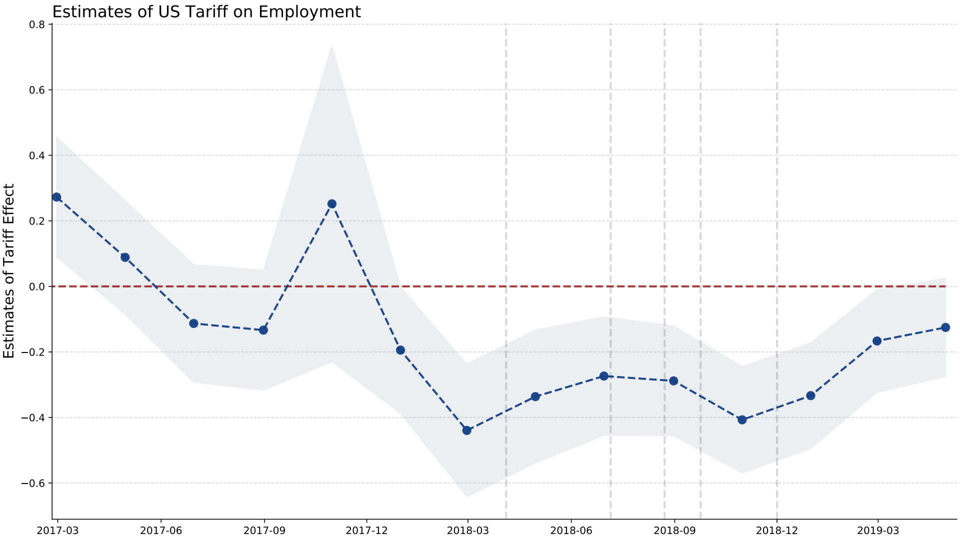
	(1)	(2)	(3)	(4)
China $\Delta \log(1+\tau_{c,t})$	**-0.54*** [0.14]		**-0.53*** [0.13]	**-0.51*** [0.13]
US $\Delta \log(1+\tau_{c,t})$		**-0.21** [0.18]	**-0.06** [0.17]	**-0.04** [0.17]
$\Delta \log MFP_{c,t}$				**-0.002** [0.00]
Time Effects	Y	Y	Y	Y
Time $\times$ Observables Controls	Y	Y	Y	Y
# Observations	43,480			
Time Period	Jan/Feb 2017 - March/April 2019			

Note: Dependent variable is 12 month, log differenced employment. County-level observations are weighted by a county's 2010 population. Standard errors are clustered at the county level and are reported in brackets.

Effect of Chinese Tariffs by Time on Total Employment



Effect of US Tariffs by Time on Total Employment



Summary of Employment Results

1. Strong evidence that Chinese retaliation decreased employment.

- Effects are strongest in goods employment.
- Connects well with the autos. Chinese retaliation changed employment opportunities and this fed into consumption.
- Sounds good, but IMHO a lot of open questions about exact mechanism.

Summary of Employment Results

2. No evidence that US tariffs helped workers. In fact, they correlate with **decreased** employment.

- And oddly it's strongest in total, not in the goods sector.

What I think is going on…these places were in decline and I'm just picking up the pre-trend (which looks like it's there and I've been unable to knock out).

- Consistent with the idea that US tariff list was selected to benefit declining US industries.
- I think it's also consistent with the non-response of consumption in protected communities.

Aggregate and Distributional Effects

People hate this (but they want it too!)

A back-of-the-envelope calculation. First, assume that relative effects are the same as absolute effects.

- Point estimates $\Rightarrow \approx$ \$3.6 billion in lost auto sales.

Then we can connect autos with total consumption via an estimate of the Engel curve.

- Aguiar and Bils (2015): estimate an elasticity of vehicle expenditure to overall expenditure to be between 0.72 and 1.
- $\Rightarrow$ aggregate consumption fell by between \$57 billion and \$80 billion.
- It's concentrated: counties in the upper quartile lost \$608 and \$845 in consumption per person vs. \$91 and \$126 decrease in the bottom quartile.

Final Thoughts

Main findings:

- Auto sales growth fell by ≈ 4 p.p. in high-tariff counties relative to low-tariff counties. Up to \$845 fall in consumption per person.
- Evidence that the fall in consumption relates to a reduction in production and labor market opportunities for those most exposed.
- No evidence that US tariffs lead to increased employment opportunities and consumption.

Open questions that I'm working on now!

- A more structural approach to properly evaluate the welfare effects.
- Do the magnitudes (trade, employment, consumption) line up?
- The role of expectations about the future?

All code to replicate (non-proprietary) results are posted at: `https://github.com/mwaugh0328/consumption_and_tradewar`

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Detail of my MFP Data. . .

	Formatted Payee Name	Delivery Address	State	zipcode9	amount	date
0	JAMES L TATUM	7641 CLEMENTINE WAY	FL	32819-4609	32.0	2019-01-29
1	JAMES L TATUM	7641 CLEMENTINE WAY	FL	32819-4609	1732.0	2019-01-29
2	R H SHACKELFORD JR	3462 HIGHWAY 14 W	AL	36003-2806	88.0	2019-02-07
3	R H SHACKELFORD JR	3462 HIGHWAY 14 W	AL	36003-2806	21382.0	2019-01-29
4	ROSA L GUY	633 ALT COUNTY ROAD 121	AL	36022-3342	15180.0	2019-01-30
5	LEON T MCCORD JR	785 COUNTY ROAD 42	AL	36051-2725	202.0	2019-01-29
6	CRAWFORD F JONES	102 CLEAR CREEK CT	AL	36067-6974	31490.0	2019-01-29
7	ROBERT R SHACKELFORD	591 SHACKLEFORD LN	AL	36003-3005	12888.0	2019-01-29
8	GAINES FARM	558 COUNTY ROAD 45 S	AL	36003-2820	49033.0	2019-01-29
9	HOME PLACE PARTNERS	1001 MCQUEEN SMITH RD S	AL	36066-7509	140711.0	2019-01-29
10	ROBERT H SHACKELFORD JR AND SONS	3462 HIGHWAY 14 W	AL	36003-2806	19072.0	2019-01-29
11	ROBERT H SHACKELFORD JR AND SONS	3462 HIGHWAY 14 W	AL	36003-2806	9046.0	2019-02-07
12	AUTAUGA FARMING CO INC	PO BOX 190	AL	36003-0190	60.0	2019-01-29
13	JOHN EALUM	2439 COUNTY ROAD 85	AL	36022-2611	1008.0	2019-01-30
14	JOE POWELL	603 WEBB DR	AL	36067-6857	13926.0	2019-01-29
15	TYLER J HILL	1558 COUNTY ROAD 42	AL	36067-8225	5608.0	2019-02-19
16	STRAIGHT WIRE FARMS LLC	PO BOX 37	AL	36003-0037	213.0	2019-01-29
17	STRAIGHT WIRE FARMS LLC	PO BOX 37	AL	36003-0037	28977.0	2019-01-29
18	JHS FARMS LLC	1001 MCQUEEN SMITH RD S	AL	36066-7509	17622.0	2019-01-29

Top Recipients: Corporate Farms Spanning Multiple States. . .

	amount	State
Formatted Payee Name		
M & M FARMS	1635440.0	[AZ, CA, CO, IA, KS, KY, MI, MN, MS, MO, MT, N...
MOORE FARMS	1466562.0	[AL, AR, IL, IA, KS, KY, MI, MS, NE, NY, TN, WA]
H & H FARMS	1329942.0	[AR, CA, CO, IA, KS, MS, NC, OK, SD, TN, TX]
JOHNSON FARMS	1050550.0	[AR, TX, CA, GA, IL, KS, MI, MT, ND, OH, SD, M...
LAKELAND PLANTING COMPANY	1027641.0	[LA, MS]
DELINE FARMS PARTNERSHIP	987768.0	[MO]
CROSSROAD FARMS	986202.0	[IN]
DELINE FARMS NORTH	975625.0	[MO]
THORNTON FARMS	962621.0	[AL, LA]
FRISCHE FARMS	959077.0	[TX]
WALKER PLACE	945952.0	[IL]
ROBERTS FARMS	926337.0	[IL, KY, NY, NC, OH]
MID-SOUTH FAMILY FARMS	914153.0	[TN]
SMITH & SONS	903108.0	[TX]
PETERSON FARMS	886413.0	[KY, MN, ND, WI]
KELLEY ENTERPRISES	874842.0	[TN]
DUE WEST FARM	840624.0	[MS]
B & B FARMS	836721.0	[AR, GA, IA, KS, MS, NC, ND, OH, TX, WY]
DELINE FARMS SOUTH	819370.0	[MO]

Simple 2×2 Diff-in-Diff

A first cut of the data...

Take 12-month log differences of autos

- Controls for any time-invariant county-level effects (in levels).
- Also addresses seasonality issues, e.g. month×county effect.

Compare average growth rates of counties with high tariff exposure versus low tariff exposure.

- High is upper quartile; low is lower quartile.
- Plot the difference in growth rates over time.

Clear Evidence that Chinese Tariffs Reduced Auto Sales (I)

China Tariffs, Auto Sales Growth, Pre and Post

China Tariff Quartile	Pre-Trade War	Post-Trade War
Upper quartile	0.0104	−0.0305
	[0.003]	[0.004]
Bottom quartile	0.0092	−0.0155
	[0.003]	[0.004]

Note: Values are 12-month log differences averaged across counties and time periods. Pre-Trade War is January 2017 to end of June 2018; Post-Trade War is July 2018-April 2019. Standard errors are reported in brackets.

Clear Evidence that Chinese Tariffs Reduced Auto Sales (II)

Unclear/Mixed Evidence on Benefits from US Tariffs

US Tariffs, Auto Sales Growth, Pre and Post

US Tariff Quartile	Pre-Trade War	Post-Trade War
Upper quartile	0.0041	-0.0224
	[0.002]	[0.004]
Bottom quartile	0.0137	-0.0211
	[0.003]	[0.004]

Note: Values are 12-month log differences averaged across counties and time periods. Pre-Trade War is January 2017 to end of June 2018; Post-Trade War is July 2018-April 2019. Standard errors are reported in brackets.

Unclear/Mixed Evidence on Benefits from US Tariffs