The Consumption and Welfare Effects of a Tariff Shock

Evidence from the US-China Trade War

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The views expressed herein are those of the author and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

This paper...

1. Measure tariff-induced changes in consumption at a narrow geographic level.

- How? I proxy consumption with the universe of new auto sales in the US at monthly frequency, county level. And correlate it with policy actions in the US-China Trade War.
- Clear evidence that Chinese retaliation had an impact. Both auto sales and employment $\searrow$ in high-tariff counties relative to low-tariff counties.

2. Use a heterogenous agent + multi-region, multi-country trade model to interpret **1.** and measure the welfare effects.

- How? Simulate and solve the model's dynamic response to tariff shocks and news about them.
- Still work in progress. Today—numerical examples and demonstrate "proof of concept."

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.

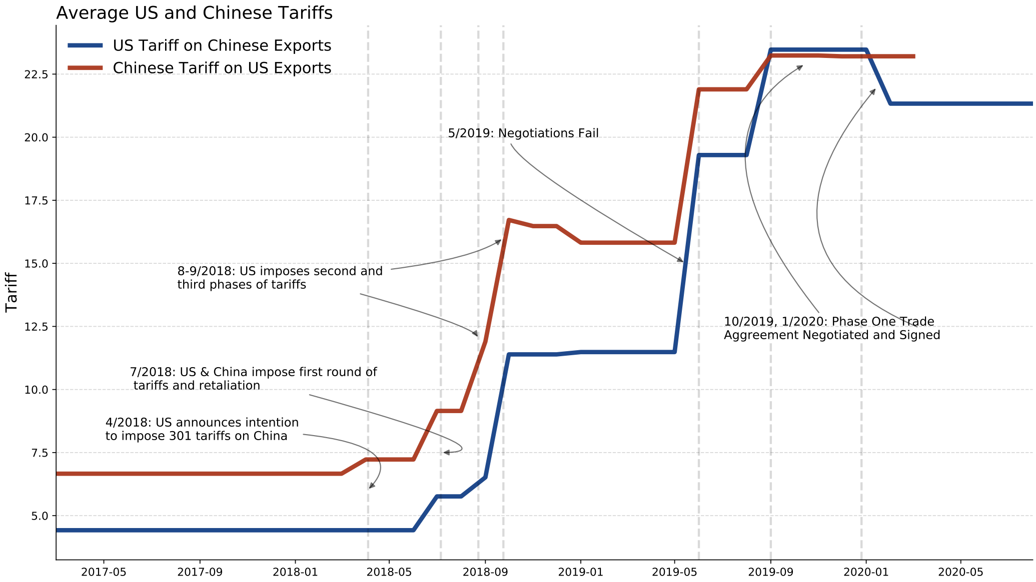
My measure of tariff exposure at the county level:

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

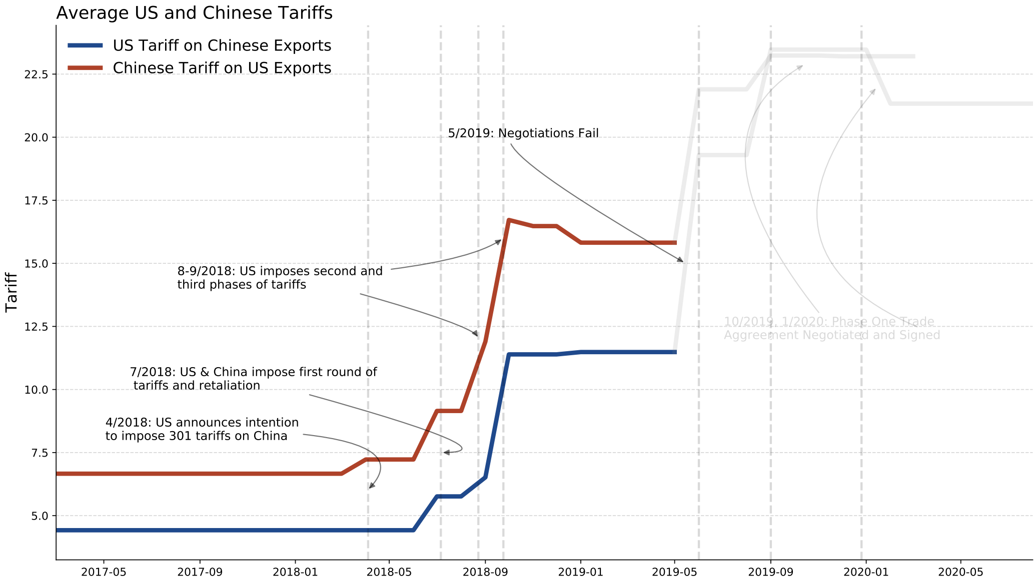
- $\frac{L_{c,s,2017}}{L_{c,S,2017}}$ = 2017 share of county c's employment in industry s.
- $\tau^{i}_{s,t}$ is the implemented tariff by country i, industry s, date t.
- Idea: if a county's employment is all in soybeans, then the county is protected and/or faces the soybean tariff.

Final point: Most my focus is on the Chinese retaliation... will show some stuff about US side.

Trade War! Average US and Chinese Tariffs



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



My Consumption Measure: New Auto Sales

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

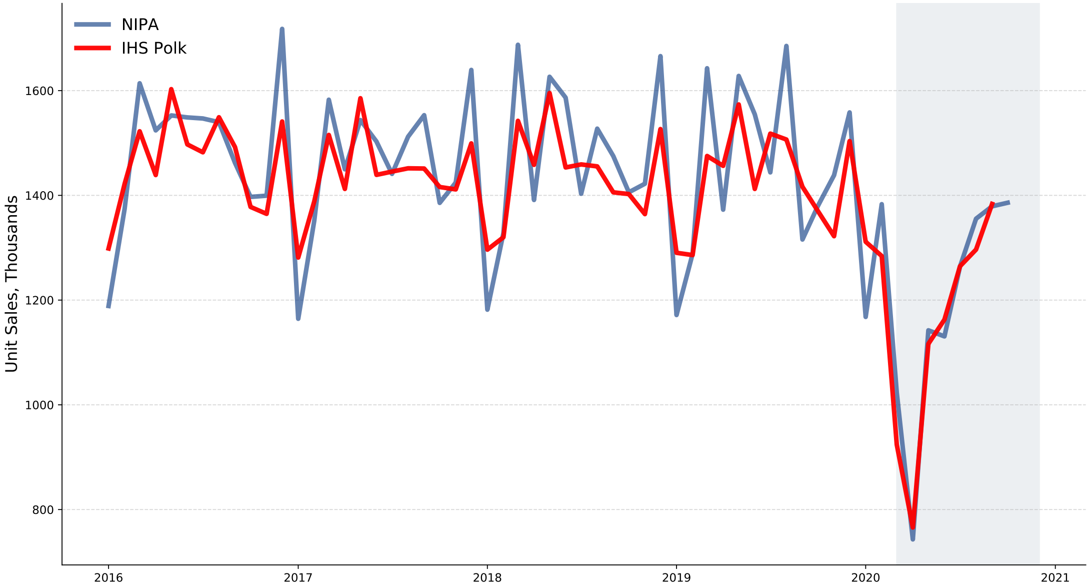
- At the county level (by local of registration, not sale),
- Monthly from January 2016 to December 2021.
- By make (e.g. Ford) and model (F-150).

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).

Aggregate Auto Sales: IHS vs NIPA



Summary Statistics

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. Employment data from BLS's Quarterly Census of Employment and Wages. Good employment equals natural resources, manufacturing, and construction.

Simple 2×2 Diff-in-Diff: 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.

Visual Diff-in-Diff: Chinese Tariffs Reduced Auto Sales (II)

Research Design

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

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.

Chinese Retaliatory Tariffs Reduced Auto Sales

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.

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

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.

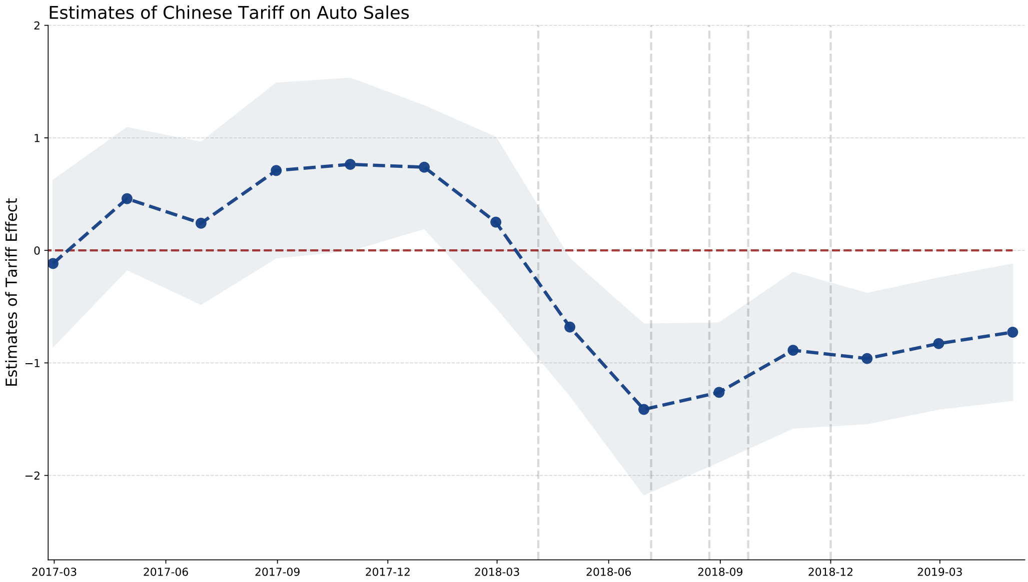
An Event Study

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

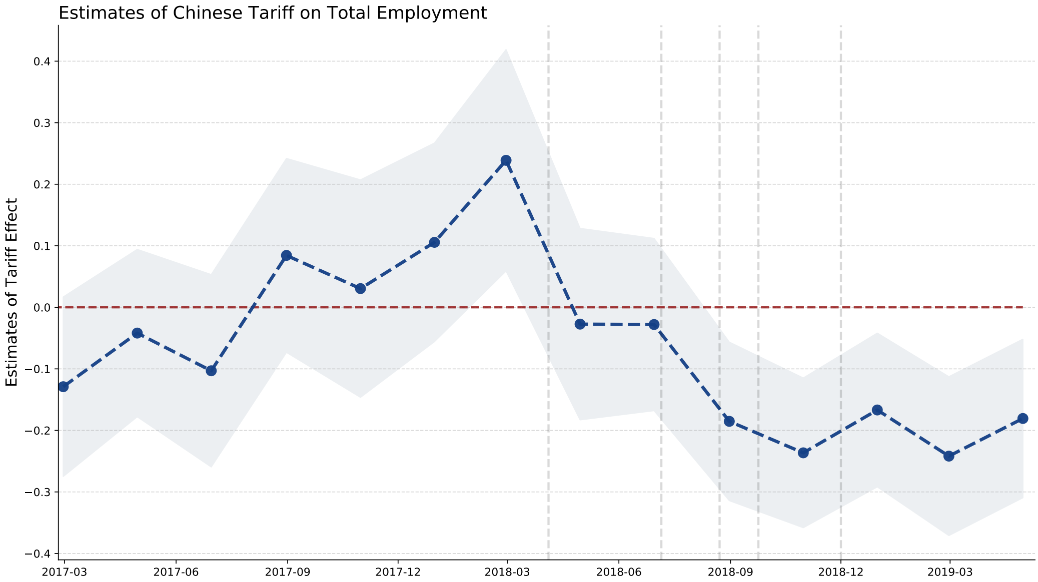
$$\Delta \log Y_{c,t} = \sum_{i \in \{ch,us\}} \sum_{y=B1,2017}^{B2,2019} \left(1\{t = y\} \beta_{i,y} \Delta \log(1 + \tau^{i}_{c,B2,2019}) \right) + \sum_{y=B1,2017}^{B2,2019} \left(1\{t = y\} X^{'}_{c} \delta_y \right) + X^{'}_{c,t} \lambda + \alpha_t + \alpha_0 + \epsilon_{c,t}$$

- 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.

Effect of Chinese Tariffs by Time on Auto Sales



Effect of Chinese Tariffs by Time on Total Employment



Pause...

Empirical findings:

- Auto sales growth fell by ≈ 4 p.p. in high-tariff counties relative to low-tariff counties.
- Evidence that the fall in consumption relates to a reduction in production and labor market opportunities for those most exposed.

Next step: Use a model to interpret and measure welfare effects

- Heterogenous agent (i.e. Bewley-Huggett-Aiyagari) + multi-region, multi-country trade model.
- Calibrate to evidence above.
- Simulate transition path to tariff shocks and news about them.

Model: Overview

Time: Discrete time, infinite horizon.

Geography and Trade: Two regions in the US ("red" and "blue") and China. A location produces a differentiated commodity as in Armington and trade occurs subject to trade costs and tariffs.

Households: They live and work in a region while facing idiosyncratic productivity shocks. They purchase and use the aggregated commodity to:

- eat it c,
- transform it into a durable good d, i.e. a "car"
- or save it as an asset a.

And households can enjoy leisure, ℓ, by choosing not to work.

Model: Households and Preferences

Mass of L_i households in each location i.

Preferences:

$$E \sum_{t=0}^{\infty} \beta^t u(c_t, d_t, \ell_t)$$

$$\text{where} \quad u(c, d, \ell) = \log\left(c^{\alpha} d^{1-\alpha}\right) + \nu\ell + \ \epsilon_{dj} + \ \epsilon_{hj}$$

- ϵ_{dj} are iid Type 1 EV shocks over option j of buying a new car or sticking with old car.
- Leisure / work is a discrete choice too.

  Either work or not ($\ell = 0$ or $\ell = 1$) where ϵ_{hj} are iid Type 1 EV shocks over those options.

Model: Cars

The stock of durable consumption evolves according to:

$$\texttt{if stay}, \quad d_{t+1} = (1-\delta)d_t$$
$$\texttt{if buy new}, \quad d_{t+1} = d(n).$$

Expenditures on durables takes the following form:

$$\texttt{if stay}, \quad e_t = 0$$
$$\texttt{if buy new}, \quad e_t = p_n d(n) - p_u d_t.$$

- $d(n)$ is quality units of a new car. This is normalized, it's not a choice variable.
- d_t is quality units of a used car; δ is the depreciation rate.
- p_n is the rate of transformation to convert one unit of non-durable consumption into a **new** car.
- p_u is the rate of transformation for used/depreciated cars.

Model: Work, Assets, and Tariff Revenue

A household's efficiency units z_t evolve according to a discrete state Markov chain. They face the wage per efficiency unit $w_{i,t}$.

Households borrow or accumulate a non-state contingent asset, a, with gross return R, and debt limit

$$a_{t+1} \geq -\phi.$$

Tariff revenue τ_r is lump sum rebated to households.

Putting this all together, a household's budget constraint is

$$w_{i,t} z_t (1 - \ell) + P_{i,t} R a_t + P_{i,t} \tau_{r,i,t} \geq P_{i,t} a_{t+1} + P_{i,t} c_t + P_{i,t} e_t.$$

where $P_{i,t}$ is the price index of the final good (next slide) in location i.

Model: Production and Trade

The final good is:

$$Q = \left\{ \sum_{k}^{M} q_k^{\frac{\theta-1}{\theta}} \right\}^{\frac{\theta}{\theta-1}},$$

where each location k produces it's nationally differentiated commodity with production technology

$$q_k = A_k N_k,$$

where N_k are the efficiency units of labor supplied by households.

Trade faces several obstacles:

- iceberg trade costs d_{nk} for a good to go from supplier k to buyer n,
- tariffs on goods that cross borders τ_{nk} which is the tariff that country n imposes on the commodity that county k produces.

And associated with this environment is the price index $P_{i,t}$ seen in the last slide.

Equilibrium

The basic idea. . .

1. Households' consumption, durables, savings, and work decisions determine goods demand and labor supply.
2. Trade determines goods supply and labor demand.

Need **1.** and **2.** to be consistent.

One detail. The asset market. Today, I'm not going to clear it (I ran out of time). In future, may do several things

1. Financial autarky, so bond market clears domestically.
2. Financial integration, so bond market clears internationally.

Calibration

Most HH parameters either standard or "jiggled around" to make it look plausible.

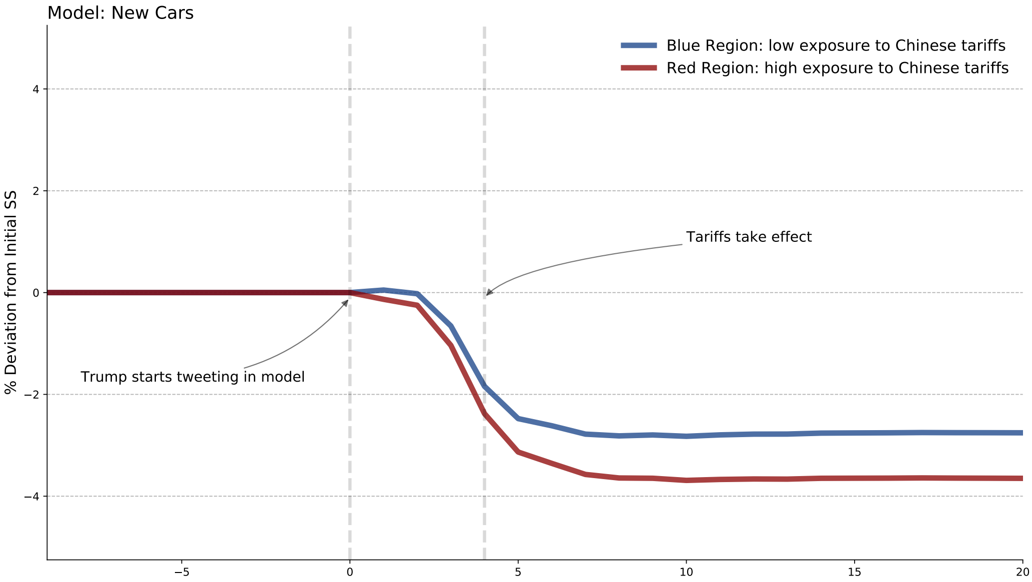
Two regions in the US (red and blue) and China.

- No trade costs, no tariffs between US regions.
- But external trade costs setup so the red region exports more to China than blue region.

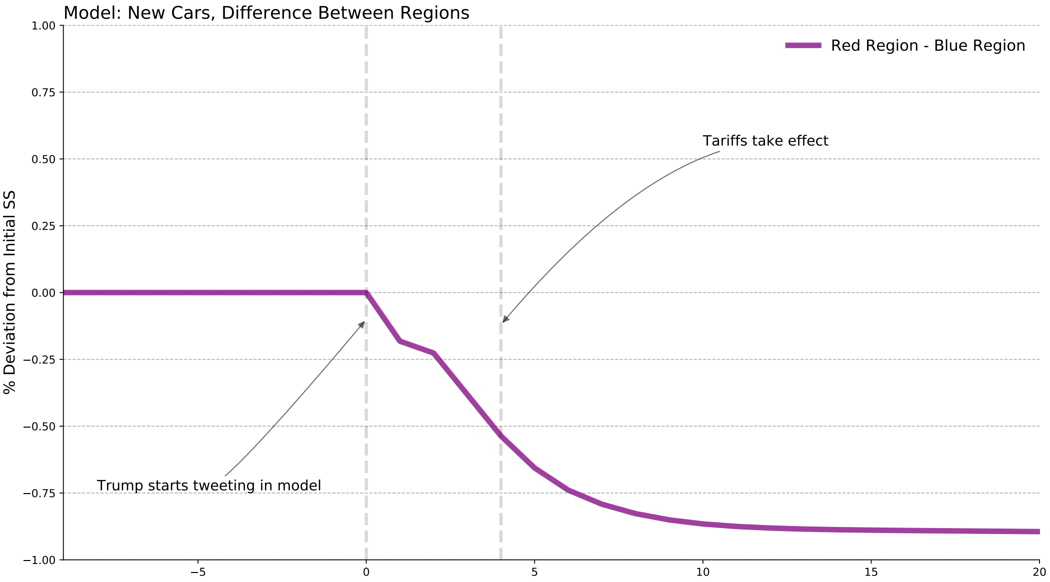
Simulate the response of the economy to observed change in tariffs.

- Give households 3 periods of advance news, similar to what happened.
- China targets red region more than blue region.
- Viewed as a permanent change (data seems to validate this!).

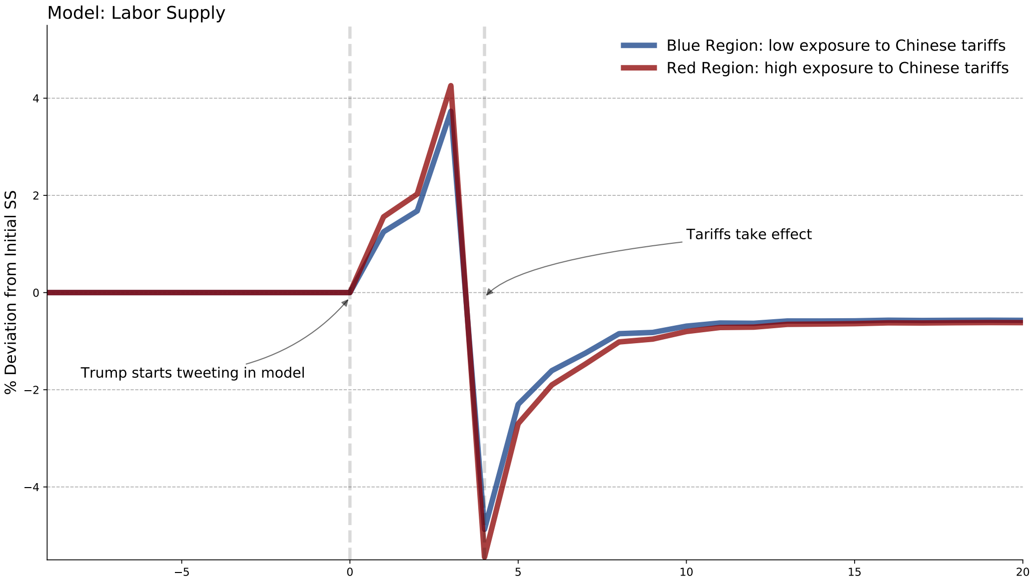
Model: New Cars



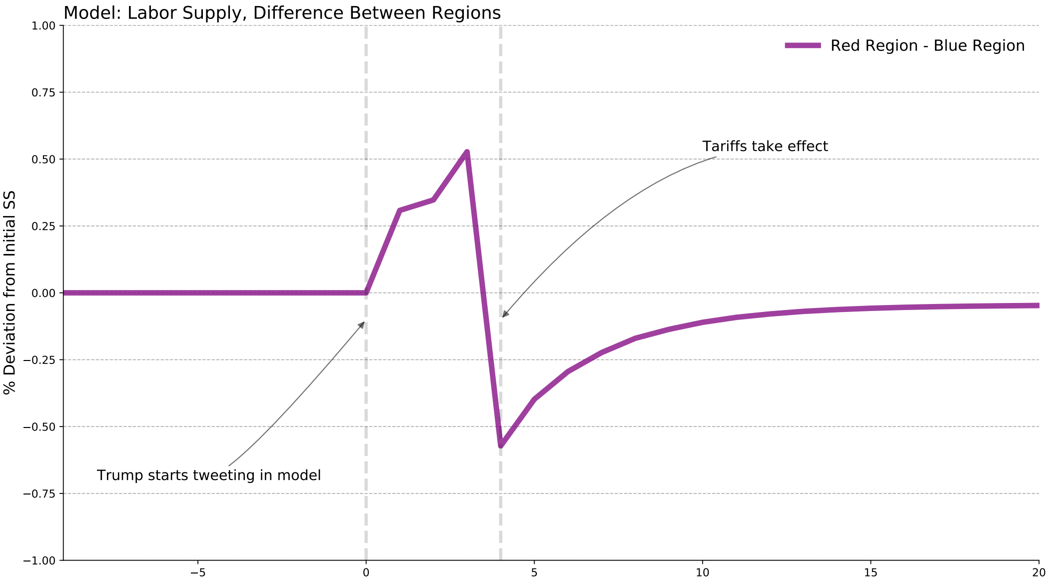
Model: New Cars, Differenced



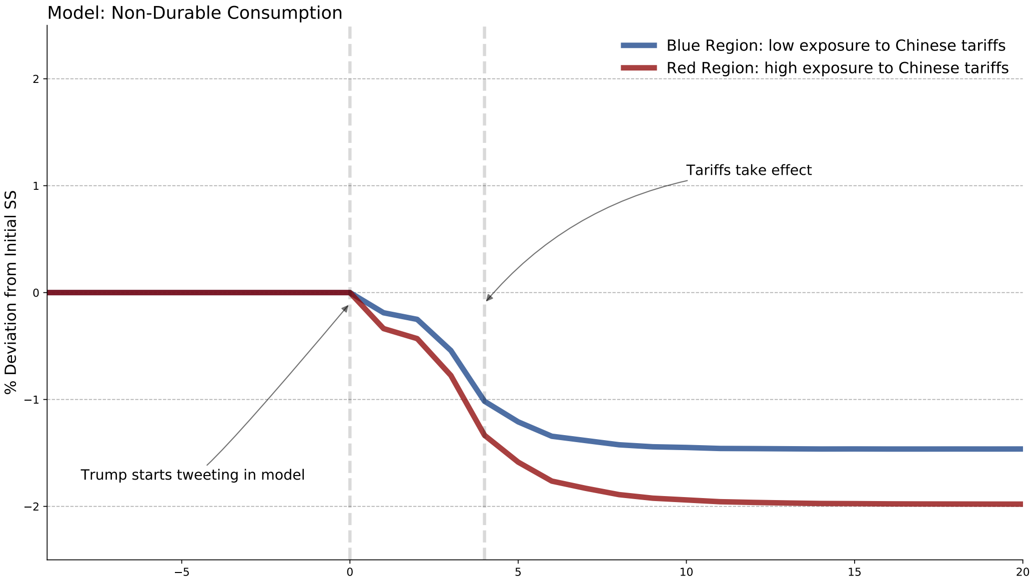
Model: Labor Supply



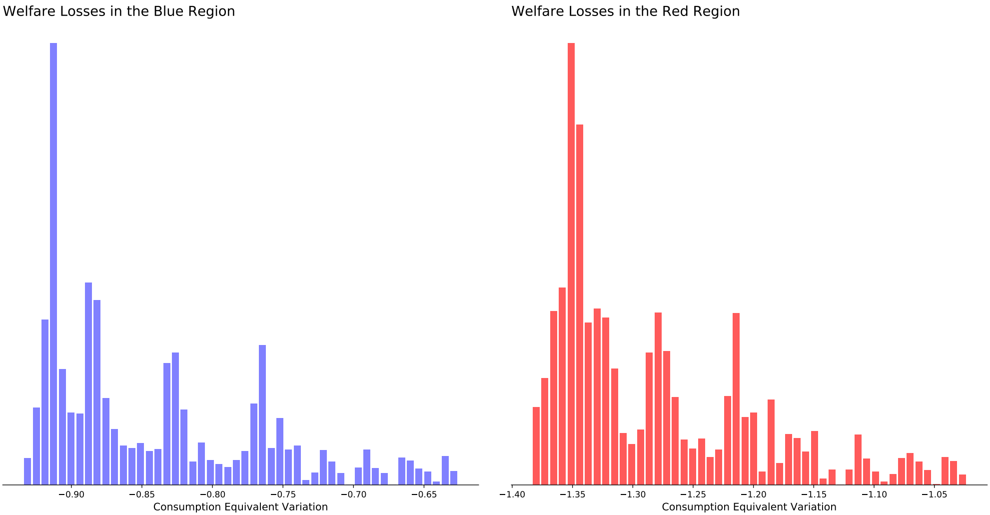
Model: Labor Supply, Differenced



Model: Non-Durable Expenditure



Welfare Losses



My Progress Report

What I've done:

- Measured tariff-induced changes in consumption at a narrow geographic level: auto sales growth fell by $\approx$ 4 p.p. in high-tariff counties relative to low-tariff counties.
- Evidence that the fall in consumption relates to a reduction in production and labor market opportunities for those most exposed.
- As of now, all this is $\approx$ consistent with what comes out of a forward-looking/ dynamic heterogenous agent + multi-region, multi-country trade model.

I'm working on now!

- A real calibration/ estimation of model and welfare analysis. Improved treatment of asset market. Talk to me in a month.
- My RA Thomas Hasenzagl and I are piecing together a public GITHUB repository with code to implement HAT models, fast and efficiently.
  - Will be in julia and python. Sorry George, no GAUSS.

References I

Bown, C., E. Jung, and E. Zhang (2019): "Trump Has Gotten China to Lower Its Tariffs. Just Toward Everyone Else," *PIIE Report*.

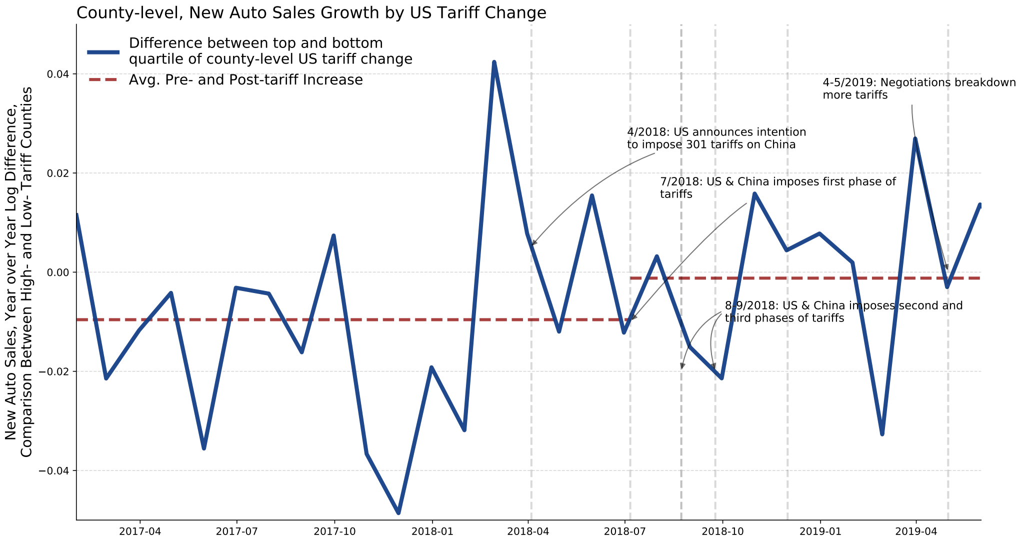
Unclear/Mixed Evidence on Benefits from US Tariffs

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



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).

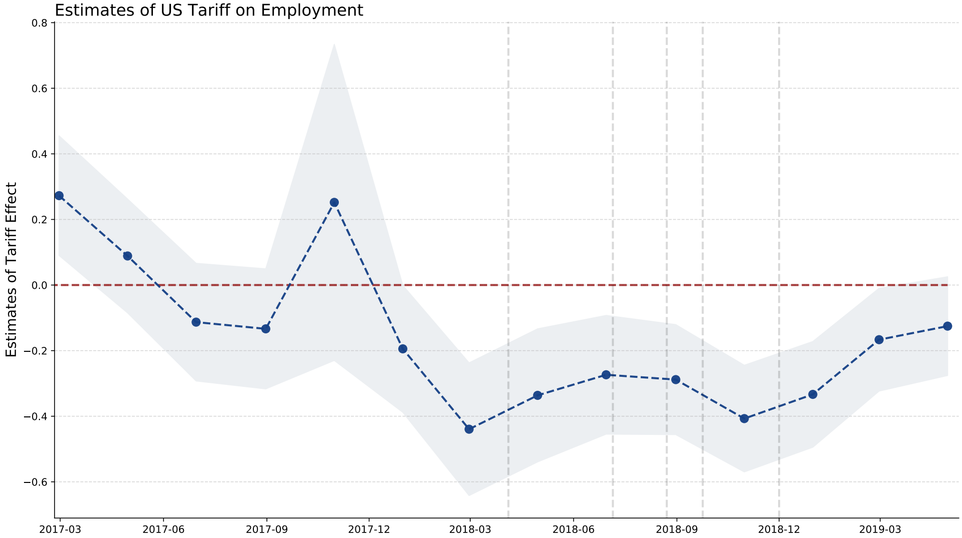
- 2018 program paid out direct $$$ based upon crop harvested.
- Trump Administration authorized up to $12 billion USD; in my data $8.6 billion was paid out.

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.

Effect of US Tariffs by Time on Total Employment



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. . .

Formatted Payee Name	amount	State
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]
VINCENT FARMS	808739.0	[AR, IN, TN]