Trade Frictions and the American Soft Power

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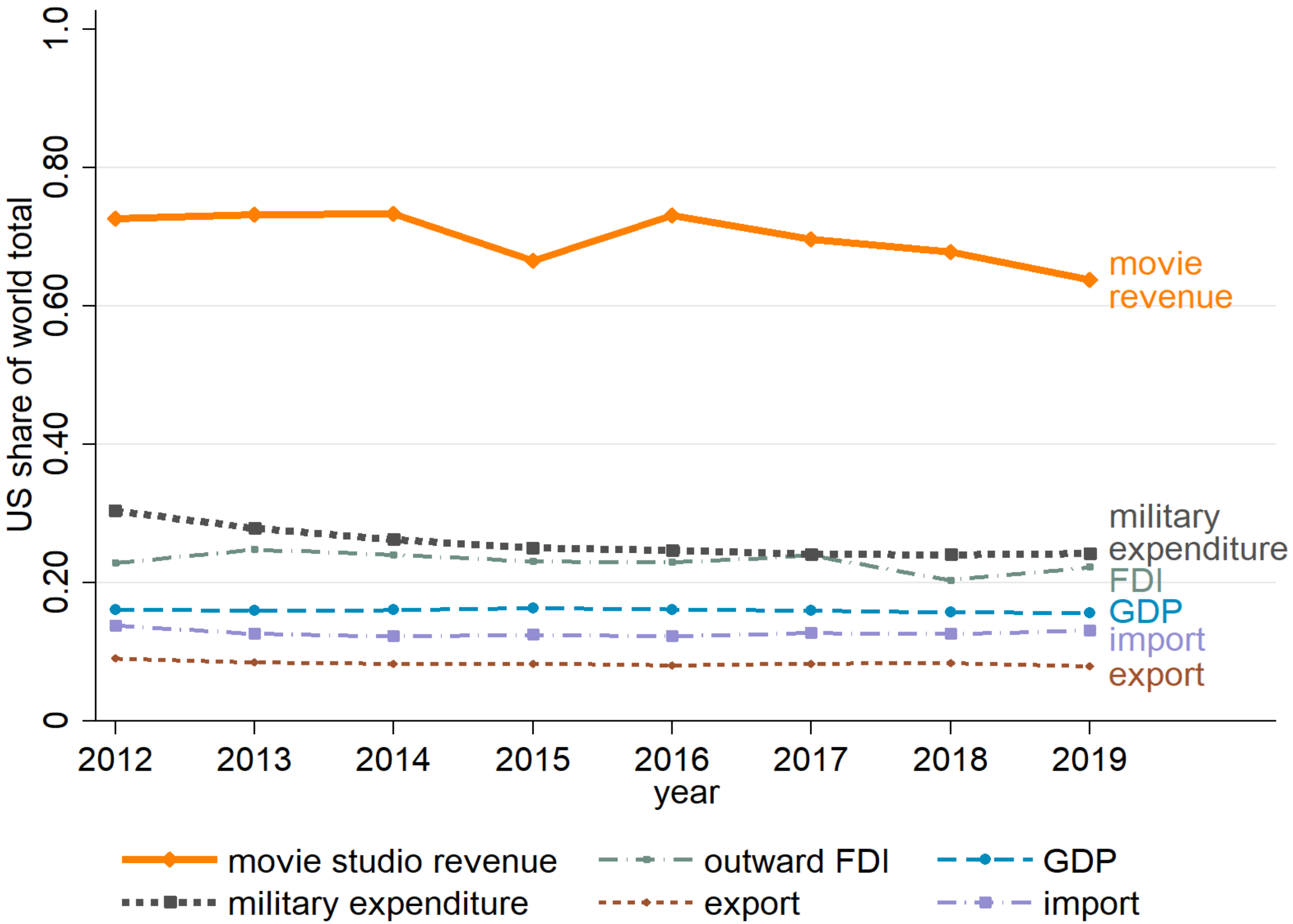
Based on Joint Research with Haichao Fan, Yichuan Hu, Lixin Tang

- The era of “de-risking”
- De-coupling, de-globalization, dis-location, “friendshoring.”

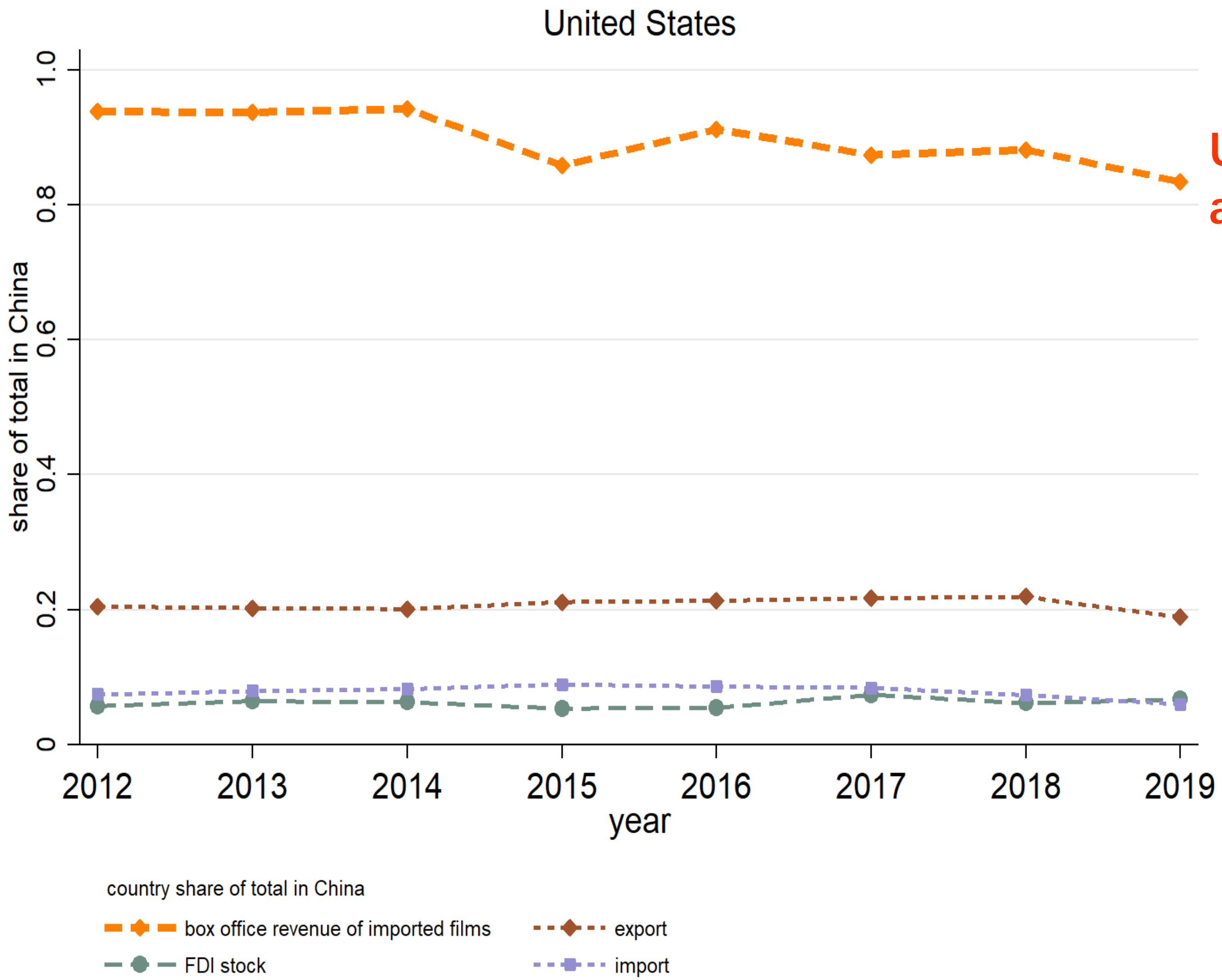
- Today’s talk: effects of trade frictions on US soft power

- How the US trade war against China – started in March 2018 under President Trump and continued under President Biden – may have affected US soft power – as reflected in the viewership of US movies and sales of US branded automobile in China

Shares of the US in the World:
Movie Revenue, Outbound FDI, Trade, & Military Expenditure



Shares of the US in China: Movie Revenue, FDI and Trade



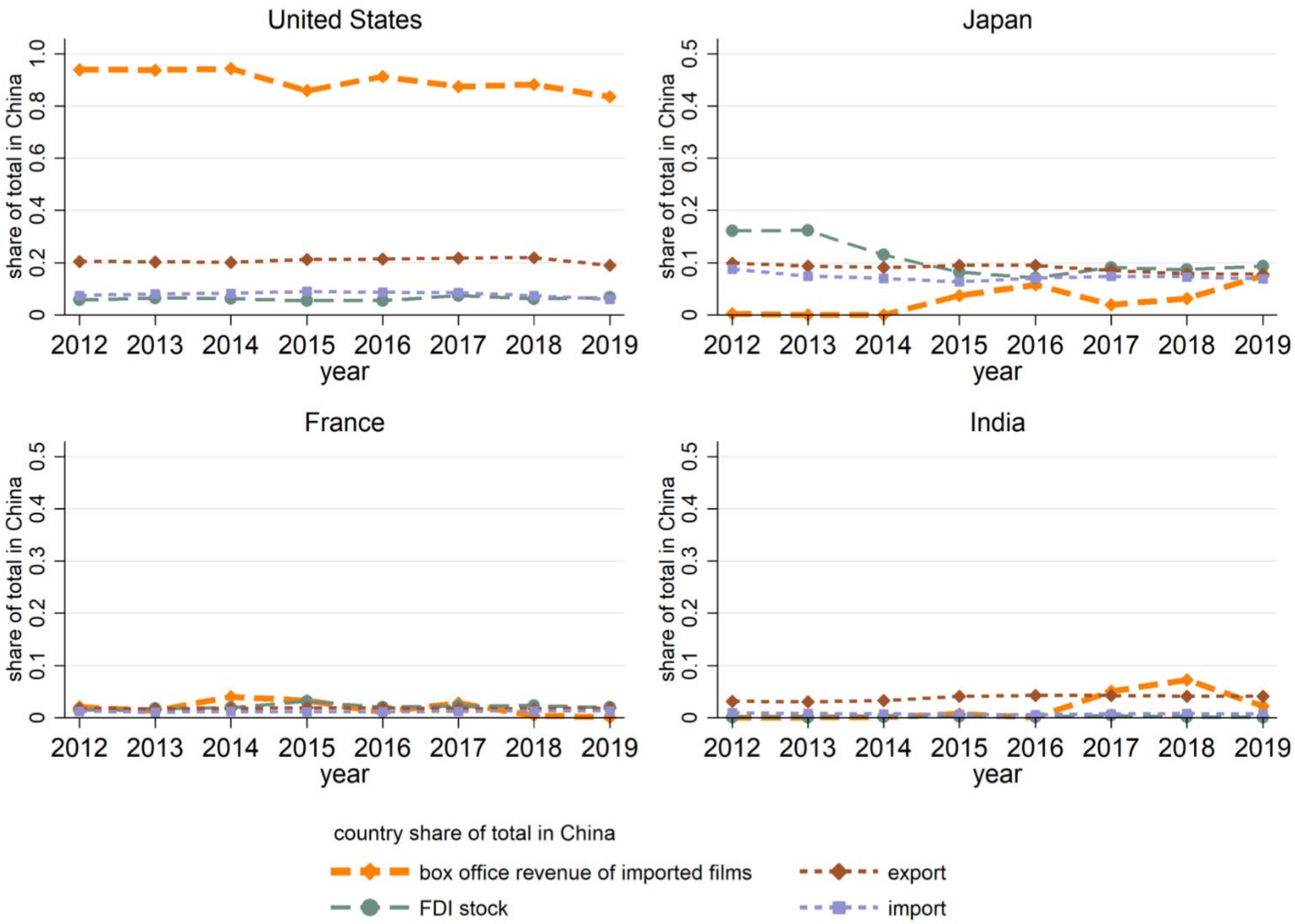
US movie revenue/
all foreign movie revenue

Chinese Exports to US/
All Chinese Exports

Chinese Imports from US/
All Chinese Imports

US FDI in China/
All FDI in China

Movie Revenue by Country in Total Foreign Movie Revenue in China: Much More Than Predicted by a Gravity Model



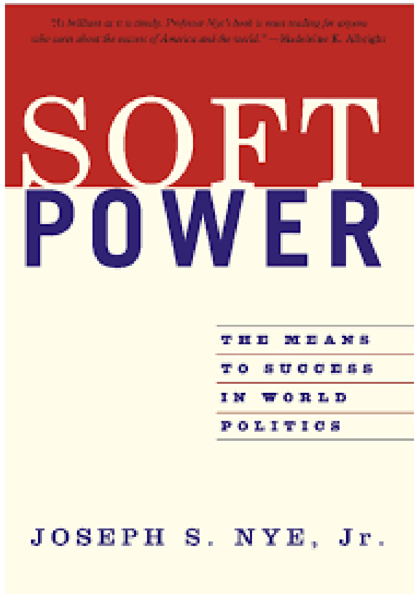
The scale of the y-axes is different by country.
Source: authors' calculation

Top selling auto models in China include many US and other international brands

Top 15 Best Selling Chinese Automakers in March 2022					
No.	Brand Model	March 2022 Units Sold	March 2021 Units Sold	Year-On-Year Increase (%)	Market Share (%)
1	FAW Volkswagen	126,131	210,879	-40.2	8
2	Changan	120,437	102,738	17.2	7.6
3	BYD	103,229	39,484	161.4	6.5
4	Geely	93,378	89,965	3.8	5.9
5	GAC Toyota	88,048	69,386	26.9	5.6
6	SAIC Volkswagen	78,018	119,300	-34.6	4.9
7	Great Wall Motor	74,071	84,423	-12.3	4.7
8	SAIC-GM-Wuling	70,841	86,201	-17.8	4.5
9	SAIC-GM	70,021	117,611	-40.5	4.4
10	Dongfeng Nissan	67,159	100,934	-33.5	4.3
11	Tesla China	65,754	35,478	85.3	4.3
12	FAW Toyota	58,239	70,392	-17.3	3.7
13	GAC Honda	54,197	76,262	-28.9	3.4
14	GAC Trumpchi	48,515	31,544	53.8	3.1
15	Dongfeng Honda	47,361	75,015	-36.9	3

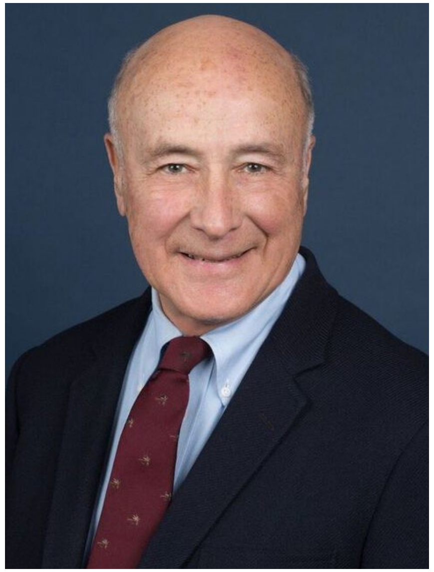
US movies (and products) as a form of soft power

- Popularity of US brands or products especially US movies in other countries has long been recognized as a form of US soft power.
  - US movies – 70% of the world movie market



- Helps to spread US values, US interests, and knowledge about US institutions, and generate sympathy/”buy-in” for US ways of looking at the world

- Soft power - “the ability to attract or co-opt others to get desired outcomes rather than coercing with threats or inducing with payments” (Nye Jr, 1990 and 2004)



- Extends and complements US “hard power” in military and economic might

Open question: effect of the trade war on US soft power

- The trade war
  - Launched by President Trump in 2018 and escalated twice more
  - Raised tariffs on imports from China to the Smoot-Hawley level
  - Rationalized as a penalty for Chinese government's unfair trade policies and practices, theft of US IPRs, and other deviations from international rules and norms

- The effect of the trade war on US soft power can be either positive or negative
  - If the citizens of the targeted country regard US trade war as a righteous action against unfair trade conduct and other transgressions by their government, they may become more attracted to US movies (and other symbols of US soft power)
    - Example: sanctions on Venezuela in 2014. US movie share went up from 87% in 2013 to 98% in 2015
  - If they regard the trade war as a bully tactic, inconsistent with the US professed ideals and a rules-based world order, they may become less attracted to US movies
- No systematic evidence on this.
- Also an opportunity to examine a new link: between service exports and tariffs

Part 1: Introduction

Research question

Basic findings

Contributions to the literature

US movies: double features = entertainment + advertisement for US valueslife

- Hollywood is called "the little State Department."
- US movies said to create a "gigantic reservoir of good will" towards the US by Wendall Wilkie (Republican presidential candidate, 1940)

- US values in US movies are often an incidental outcome of directors or screen writers' choice, but not entirely

The US government has a hand in some of the major blockbusters

- US Department of Defense (DoD) has an "industrial policy" for movies that portray US armed forces in a positive light.
- Its Hollywood Liaison Office can arrange free (or low-cost) use of tanks, ships, military bases, and even troops in movies that DoD supports, which includes several Oscar winning ones.
- The Central Intelligence Agency (CIA) also has a cooperation program with movie studios and can provide "advice and help."
- It is also said to have succeeded to getting movie directors to alter scripts to its liking ("to be more accurate" and "to avoid disclosing secrets").
- An example is Zero Dark Thirty, a Golden Globe and Oscar winner.

Overview: What do we do? (1)

- Explore regional variations
  - City-month level exposure to Trump tariff increases
  - City-month or theater-month level box office performance of US movies
- Key findings:
  - Exposure to US tariffs reduces audience appetite for US movies
    - Increase in Trump tariff exposure by 1 s.d. -> 5.6% reduction in US movies
    - loss of 3.0 billion yuans due to the trade war
  - Control for income effect
    - No change for other foreign movies and a weak increase for Chinese movies
  - Control for the government effect
    - No change in quotas/tariffs on US movies
    - No more government commentaries in more exposed regions

Overview: What do we do? (2)

- Similar findings on sales of US branded automobile:

  - Exposure to US tariffs reduces consumer appetite for US cars

  - The effects go beyond reduced imports (of US cars)

  - Locally made US branded cars also experience a decline in sale in regions more exposed to US tariff increases

Overview: What do we do? (3)

- Complementary evidence from Baidu search results
- Baidu – dominant Chinese-language search engine in China similar to Google in the US

- Key findings:
  - More awareness of or concern for trade war in more Trump tariff-exposed regions
  - Reduction in search intensity for US movies, US tourist destinatons, US-branded sports shoes, and US colleges/grad schools in more Trump tariff-exposed regions
  - No comparable changes in other foreign varieties.

Some evidence on heterogeneity

Some indirect evidence that the trade war has a smaller negative effect on affluent Chinese's attitude towards US

Sorting movie theaters by average ticket prices

Viewers in fancier theaters exhibit a smaller reduction in US movie viewership than those in less fancier theaters when comparing regions with more or less exposure to the Trump tariffs

Sorting cars by unit prices

Lower priced US cars exhibit a stronger decline in sales in more trade war exposed regions.

Comparing search for US colleges vs US movies or shoes

Baidu search intensity for US colleges exhibits a smaller reduction than that for US movies (when comparing regions with more or less exposure to the Trump tariffs)

Part 2: Institutional Background

the trade war

US movies in China

2018-2019 US-China trade war

- March 2018: President Trump asked USTR to apply tariffs on $50-60 billion of Chinese exports, citing Section 301 of the Trade Act of 1974.
  - First wave came into effect in July and August of 2018.
- Two additional rounds of tariffs, covering $200 billion and $272 billions of Chinese goods, in July 2018 and August 2019, respectively.
- China retaliated with tariffs on $185 billion of US goods.
- January 2020 a "Phase One" agreement signed between the US and China, signaling a "truce" in the trade war.
  - most tariffs remained in place.

Are the US actions justified under the international law?

WTO ruling (Sept 2020)

https://www.bbc.com/news/business-54168419

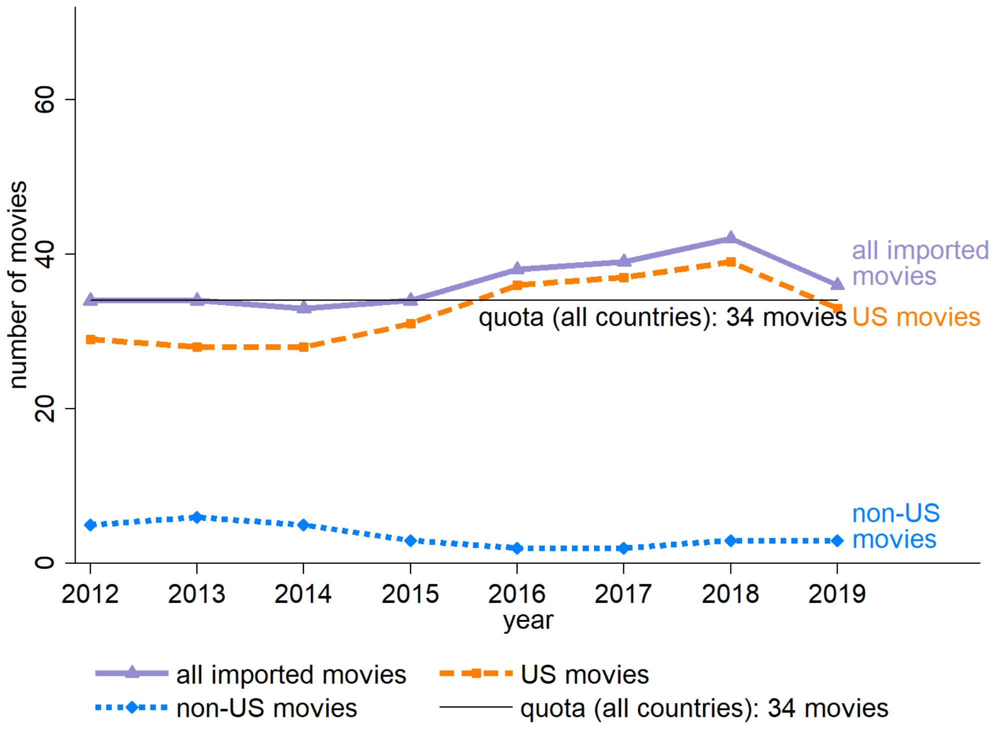
US tariffs on Chinese goods are "inconsistent with US obligations under WTO Articles 1 (MFN principle) and 2 (tariff commitment)"

In other words, in the judgement of the WTO dispute settlement panel – appointed by WTO Director General and consisting of WTO members other than China and the US – the US trade war actions are illegal under WTO rules

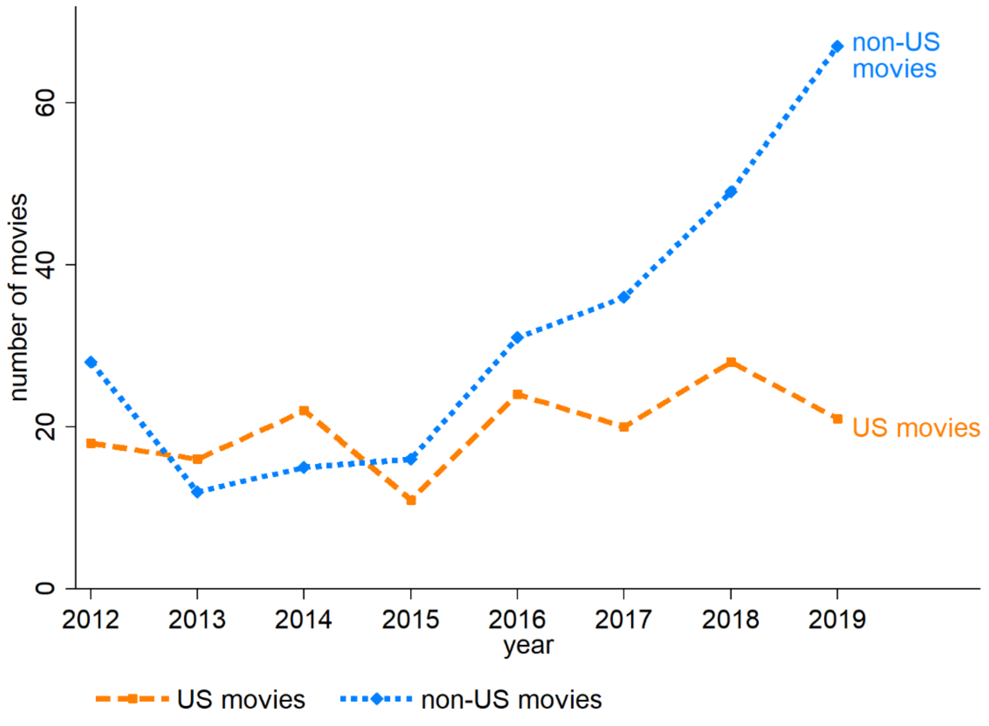
This could make the US trade war different from US sanctions on Venezuela in 2014 or Russia in 2022

- **Background on US movies in China**
- Imported movies = revenue sharing + flat fee
  - "Revenue sharing" used for major Hollywood movies
- Annual quota on "revenue sharing movies" = 34
- No limit on flat fee or "buy-out" movies
- Imports done by two state-owned companies
- Theaters are 98.8% privately owned
- No tariff increase or quota decrease on US movies during the trade war
  - # US revenue sharing movies in 2018 was above the quota, and higher than any Obama year
  - It fell back to the quota in 2019, but still higher than most Obama years.
- No special within-border taxes US movies
- Movie distribution to theaters is digital
- High frequency and extensive geographic coverage

Number of Imported movies over 2012-2019



(a) revenue-sharing imports



(b) flat-fee imports

Notes: Calculations by the authors based on data from Entgroup.

Part 3

Specification

Data

Baseline results

Robustness checks

Empirical specification: long difference (2017-19) or panel

- Theater-month level year-over-year changes

$$\tilde{\Delta}\log y_{ict} = \beta_0 + \beta_1 \tilde{\Delta} tariff_{ct} + \beta_2 \tilde{\Delta} X_{ct} + \phi_t + \phi_i + u_{ict} \tag{1}$$

  - where $\tilde{\Delta}\log y_{ict} = \log y_{ict} - \log y_{ic(t-12)}$ denote either long difference (2017-2019) or 12-monthly year-on-year change in log y in theater i.
  - y_{ict} could be local income or labor market outcome, or a measure of box office performance
  - $tariff_{ct}$ is a measure of exposure to US tariff.
- The city-specific tariff exposure tariff$_{ct}$ according to

$$tariff_{ct} = \sum_{k=1} \left(\frac{L_{c0}^k}{L_{c0}} \cdot tariff_t^k\right) \tag{2}$$

  - where $tariff_t^k$ is the US tariff on sector k in month t, L_{c0}^k and L_{c0} are the initial sector k and total employment for city c, respectively.
- Two-way cluster at the city and region-month level.

Validity of the Bartik (shift-share) instrument in the current context

To be provided in the subsection on robustness checks

Regional variation in the instrument is not dominated by shocks in a small number of sectors

- Removing top 3 sectors with the largest Rotemberg weights do not alter the result

Balance tests suggest that the local sector shares not endogenous

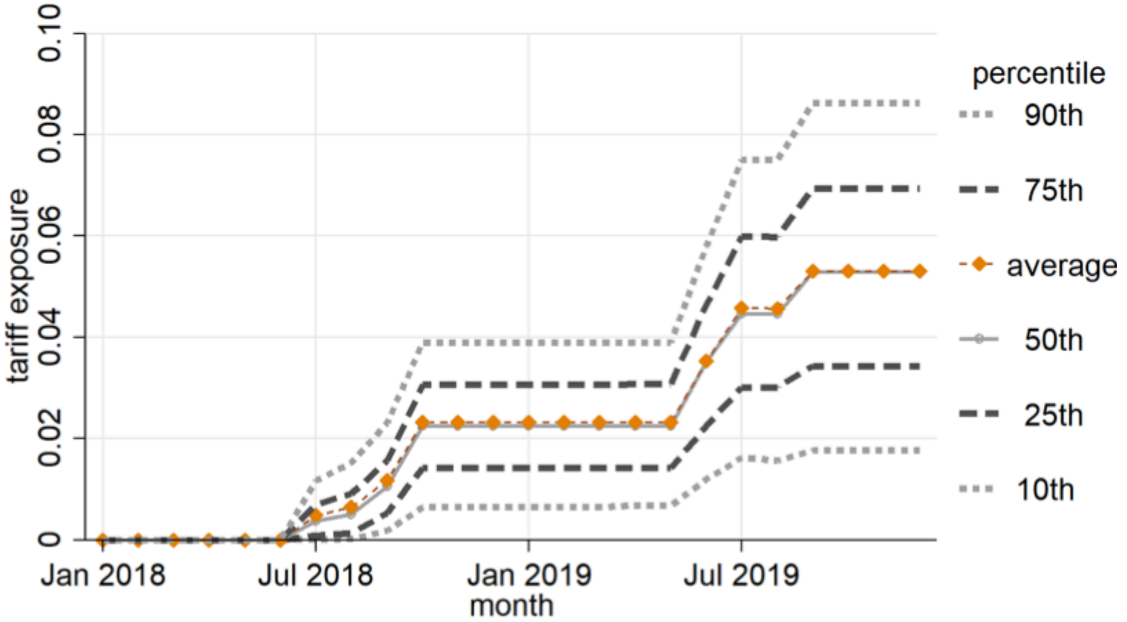
Data

- Data on exposure to US tariffs
  - US tariffs: product lists announced by USTR at each round of tariff increases, converted to CIC industries
  - Local industry composition of employment: 2008 Economic Census of China.
- Data on box office receipts
  - total revenue, number of tickets sold, number of screening sessions, and attendance rate
  - aggregated for each movie and theater by month 2017-2019.
- Other city-level data
  - weather, air pollution, city-level socioeconomic characteristics,
- Final data set: 323865 observations at the theater-month level; 10057 movie theaters in 325 cities

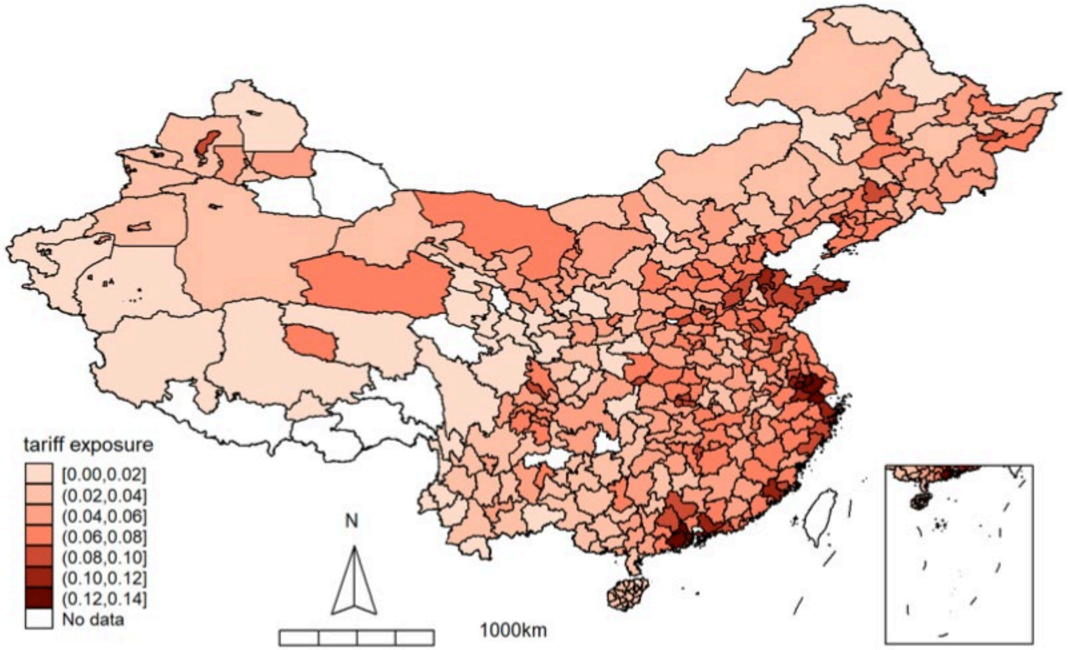
The tariff measure

Tariff exposure over time and across cities

(a) over time



(b) across cities



Notes: Calculations by the authors. Panel A plots the tariff exposure over time while Panel B reports the tariff exposure across cities in December 2019.

Table 1. summary statistics of key variables

Variables	mean	median	std. dev.	N
movie revenues				
US revenue (thousand yuan)	188.5	66.7	341.8	323865
CN revenue (thousand yuan)	313.3	124.4	488.0	323865
total revenue (thousand yuan)	534.5	298.1	673.1	323865
$\tilde{\Delta}$ log US revenue	-0.230	-0.313	1.154	197715
$\tilde{\Delta}$ log CN revenue	0.011	0.053	1.160	197715
$\tilde{\Delta}$ log total revenue	-0.070	-0.088	0.701	197715
cumulative tariff exposure				
By year				
2018	0.0078	0.0075	0.0048	325
2019	0.0382	0.0372	0.0194	325
By half year				
2018h2	0.0156	0.0149	0.0096	325
2019h1	0.0254	0.0246	0.0137	325
2019h2	0.0511	0.0502	0.0253	325
For selected month				
2018 December	0.0234	0.0226	0.0129	325
2019 June	0.0355	0.0352	0.0180	325
2019 December	0.0535	0.0533	0.0269	325

Notes: Panel A reports the summary statistics of monthly movie revenues in the theater-level regression sample. Movie revenues are measured in thousand yuan and covers 10057 theaters. The variables denoted by $\tilde{\Delta} \log y$ refer to the 12-month differences of $\log y$ and covers 9983 theaters. Missing values of $\tilde{\Delta} \log y$ can result from zeros in y, or if a theater is less than 12 months old. Panel B reports the summary statistics of city-level tariff exposure by year, by half-year, and for selected months.

Table 2: Effects of Tariff Exposure on the Local Economy

	(1)	(2)	(3)	(4)
yearly changes in	log export	export/GDP ratio	log GDP	log GDP per capita
$\tilde{\Delta}$ tariff exposure	-5.763***	-0.622**	-2.054***	-2.076***
	(1.877)	-0.622**	(0.658)	(0.662)
R-square	0.352	0.594	0.572	0.569
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N cities	321	321	325	325
N obs	642	642	650	650

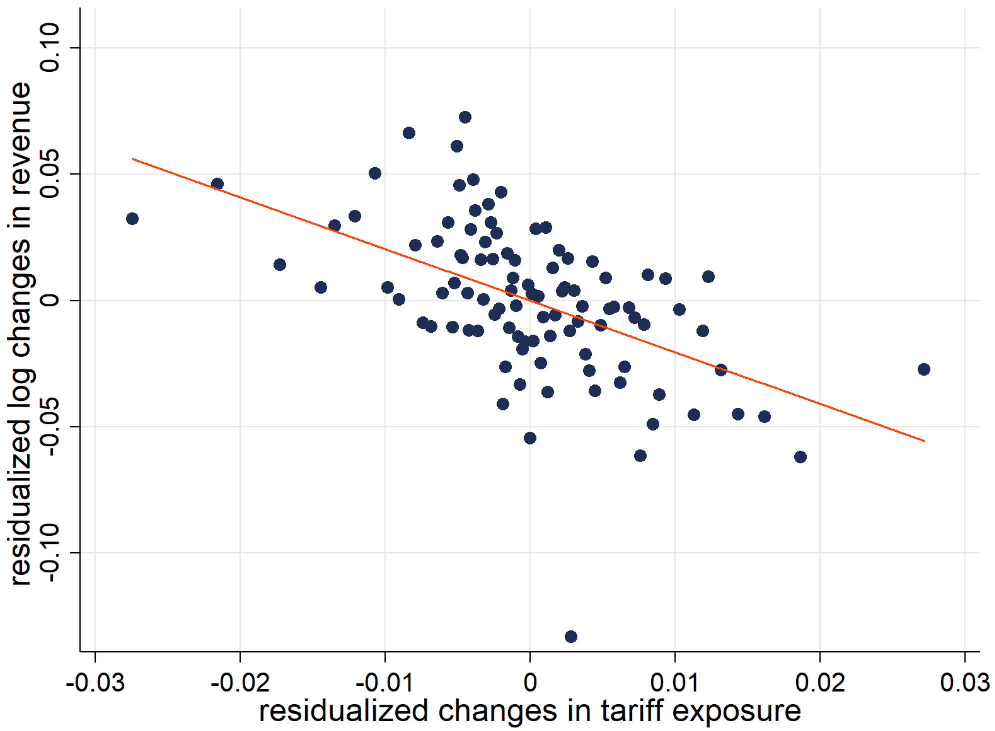
Notes: All regressions include year and city fixed effects. Standard errors in parentheses are clustered by city. ***p < 0.01 **p < 0.05*p < 0.1.

Table 3: Effects of Tariff Exposure on US Movie Revenue: City-level Regressions

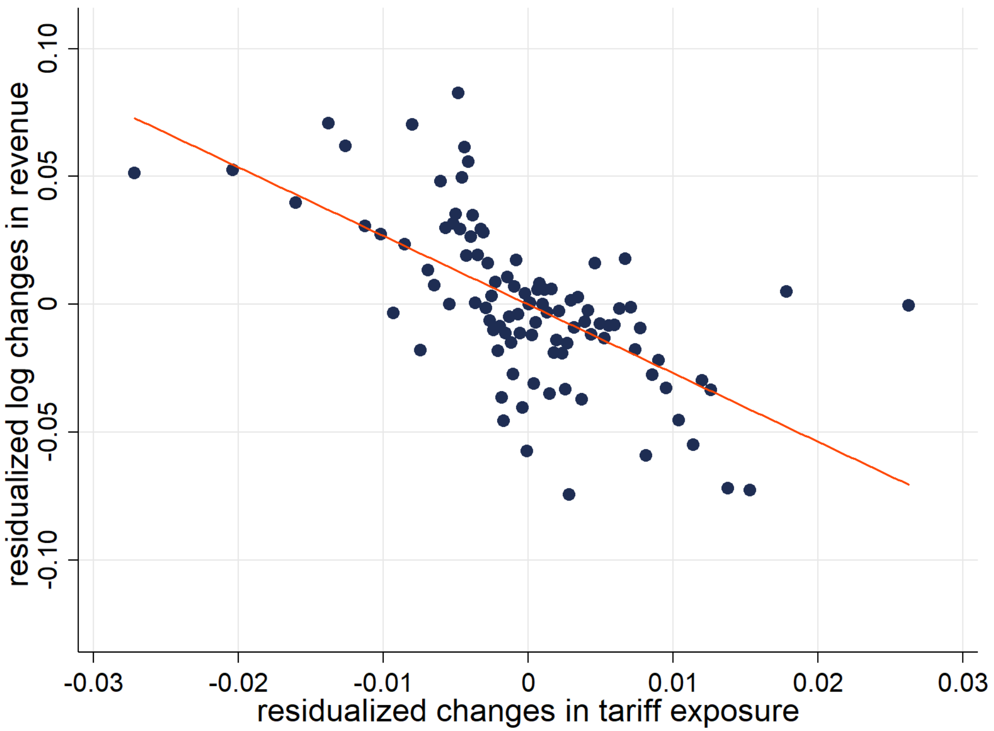
	(1)	(2)	(3)	(4)
A. Single Differencing				
	2017h2-2018h2	2018h1-2019h1	2018h2-2019h2	2017h2-2019h2
Δ tariff exposure	-0.479	-0.951***	-1.006***	-0.507*
	(0.433)	(0.321)	(0.333)	(0.301)
Δ log GDP pc	0.033	0.250***	0.056	0.091**
	(0.040)	(0.070)	(0.043)	(0.045)
R-square	0.046	0.107	0.026	0.027
N obs	325	325	325	325
B. Panel Regressions				
	semi-annually		monthly	
$\tilde{\Delta}$ tariff exposure	-0.915***	-1.723***	-1.291***	-2.077***
	(0.254)	(0.331)	(0.353)	(0.589)
$\tilde{\Delta}$ log GDP pc	0.071**	0.069**	0.045	0.026
	(0.027)	(0.027)	(0.049)	(0.049)
R-square	0.871	0.922	0.962	0.968
time FE	Yes	Yes	Yes	Yes
city FE	No	Yes	No	Yes
N cities	325	325	325	325
N obs	1300	1300	7794	7794

Notes: All regressions control for changes in log number of theaters. Each city-level observation is weighted by the number of theaters of the city in 2017. Panel A reports robust standard errors in parentheses. Standard errors in Columns 1 and 2 of Panel B are clustered by city, while those in Columns 3 and 4 are two-way clustered by city and region-month. ***p < 0.01, **p < 0.05, *p < 0.1.

Bin-scatter plots for baseline regression



(a) city-level



(b) theater-level

Notes: Panels (a) and (b) presents the binscatter plots of residualized variables corresponding to the city- level regression in Column 4, Panel B of Table 3, and the theater-level regression in Column 4 of Table 4, respectively. For each of the plots, we group the observations into 100 equal-sized bins according to residualized tariff exposure. For the city-level plot, the residualized variables are obtained from regressions of the relevant variables on month and city fixed effects, and changes in log GDP per capita. For the theater- level plot, the residualized variables are obtained from regressions of the relevant variables on month and theater fixed effects and a vector of baseline city controls.

Part 3: Evidence from automobile sales in China

Annual vehicle registration data by city and vehicle model from 2017 to 2019 for all vehicle models.

- year-month and city of registration,
- the make and model of the vehicle, as well as key characteristics such as transmission type, fuel type, and engine size.
- supplement the car registration data with information with another dataset on detailed vehicle attributes including Manufacturer Suggested Retail Prices (MSRPs) by model.

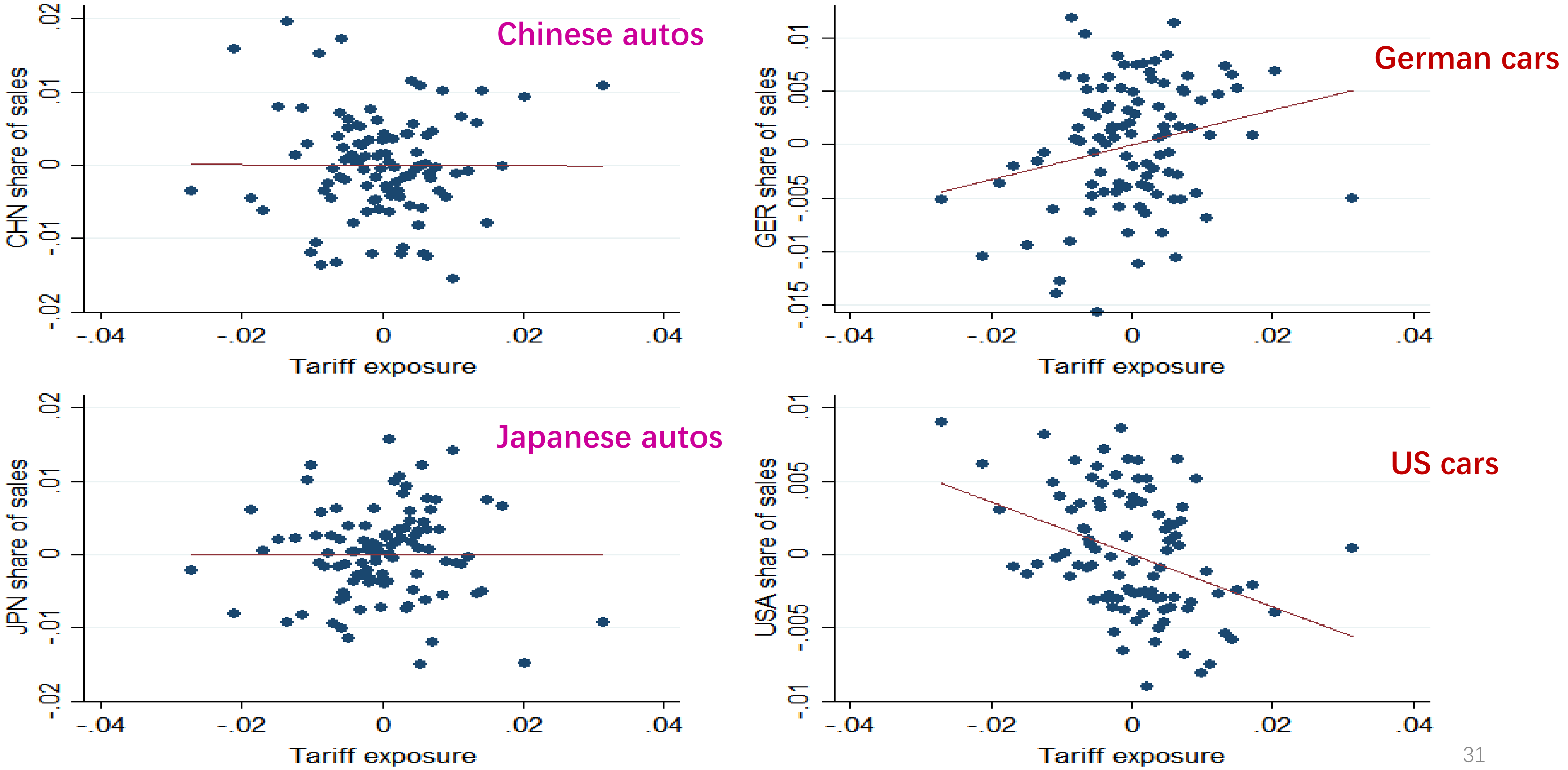
Analyze the effects of tariff exposure on cars from different countries.

- Most foreign brands are produced by joint-ventures inside China.
- We assign these joint-venture cars to the origin of the brand.
- (i.e. “Ford” is American even if it is produced by a joint-venture inside China.)

Change in market shares in automobile sales by region

	(1) CHN	(2) GER	(3) JPN	(4) OTH	(5) USA
A. Long Difference (Changes between 2017 and 2019)					
			Δ share of total		
Δ tariff exposure	-0.004	0.338***	0.034	0.051	**-0.419*****
	(0.171)	(0.111)	(0.124)	(0.082)	**(0.114)**
Δ log GDP pc	-0.035	0.047**	-0.028	0.003	**0.014**
	(0.025)	(0.019)	(0.017)	(0.010)	**(0.015)**
R-square	0.043	0.129	0.089	0.014	**0.193**
N obs	325	325	325	325	**325**
B. Panel Regressions					
			share of total		
tariff exposure	-0.004	0.163	-0.001	0.021	**-0.179****
	(0.151)	(0.100)	(0.128)	(0.053)	**(0.068)**
log GDP pc	-0.029	0.035***	-0.015	0.006	**0.004**
	(0.018)	(0.010)	(0.014)	(0.008)	**(0.011)**
R-square	0.887	0.804	0.846	0.548	**0.743**
city FE	Yes	Yes	Yes	Yes	**Yes**
month FE	Yes	Yes	Yes	Yes	**Yes**

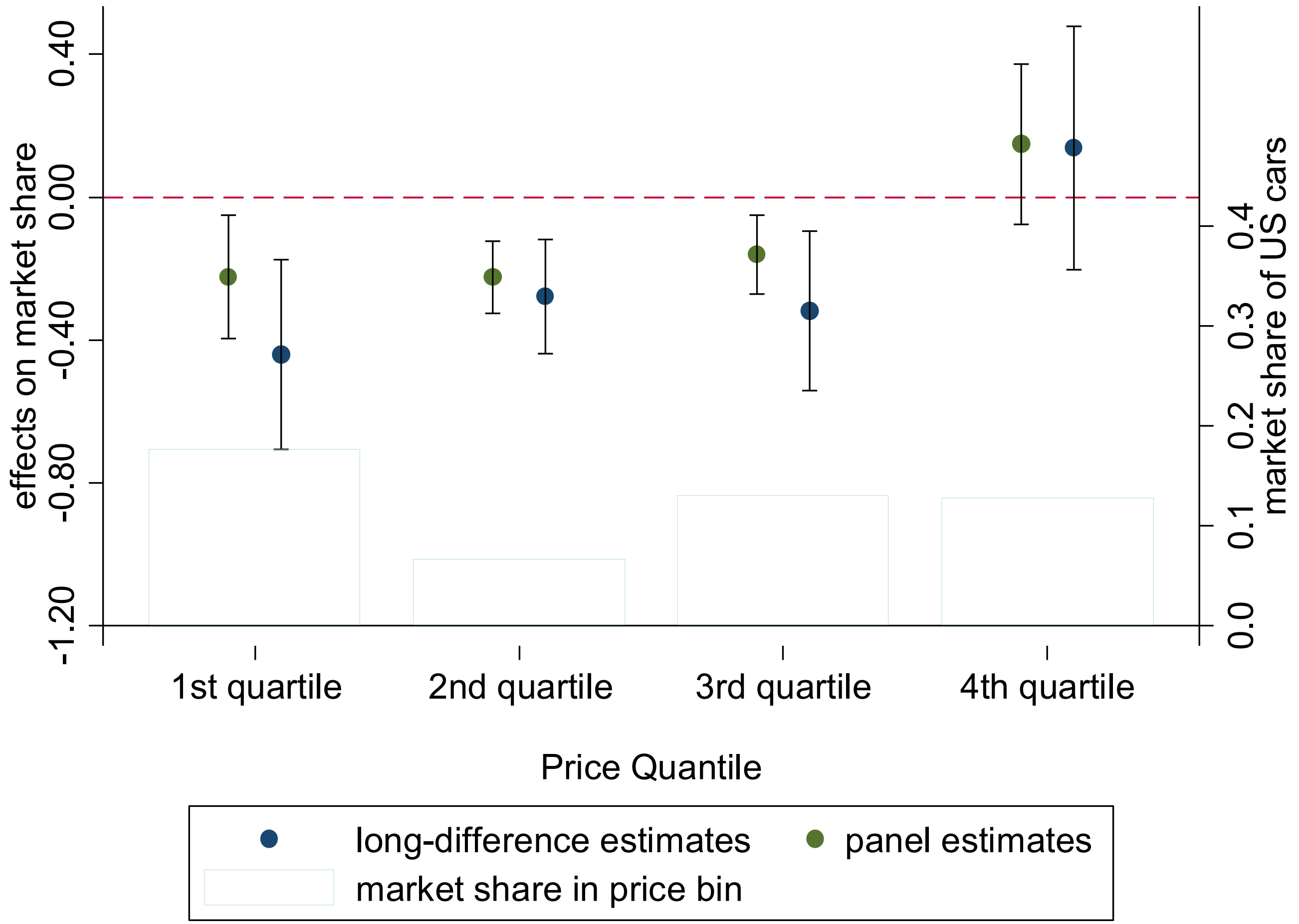
Figure about effects on market share



US automobile sales by price category

	(1)	(2)	(3)	(4)
Price Quartile	1st quartile (lowest)	2nd quartile	3rd quartile	4th quartile (highest)
A. Long Difference (Changes between 2017 and 2019)				
	Δ share of cars in price quartile			
Δ tariff exposure	-0.441***	-0.278***	-0.319**	0.137
	(0.161)	(0.097)	(0.135)	(0.207)
Δ log GDP pc	0.074***	-0.017	-0.048**	-0.091***
	(0.029)	(0.015)	(0.019)	(0.032)
R-square	0.353	0.343	0.358	0.234
N obs	325	325	325	325
B. Panel Regressions				
	share of cars in price quartile			
tariff exposure	-0.224**	-0.224***	-0.161**	0.148
	(0.105)	(0.061)	(0.066)	(0.136)
log GDP pc	0.041**	-0.013	-0.042***	-0.057**
	(0.020)	(0.012)	(0.016)	(0.027)
R-square	0.794	0.697	0.778	0.566
city FE	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes
N obs	7475	7661	7676	7778

Figure about effects by price quartile

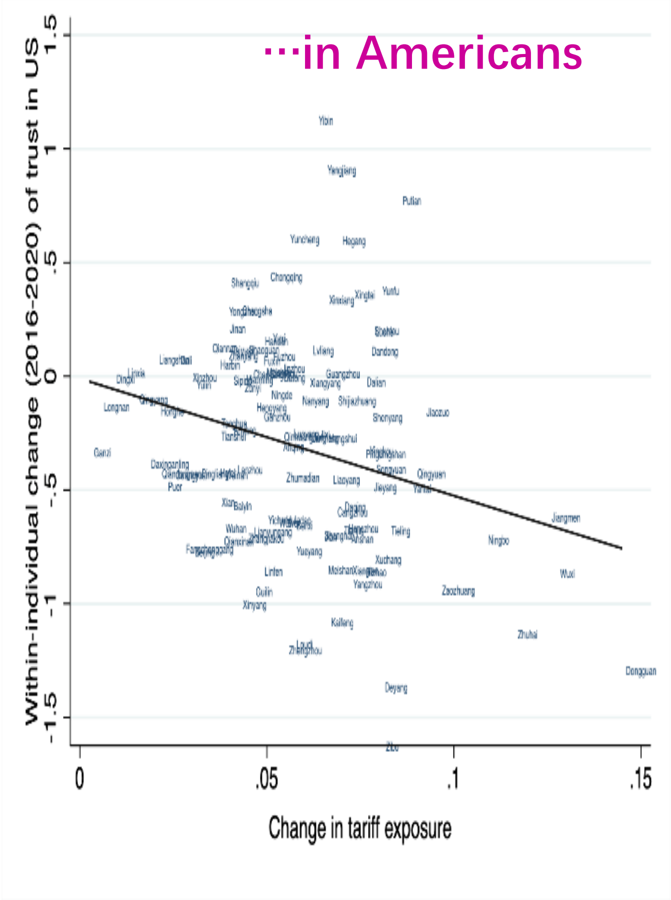


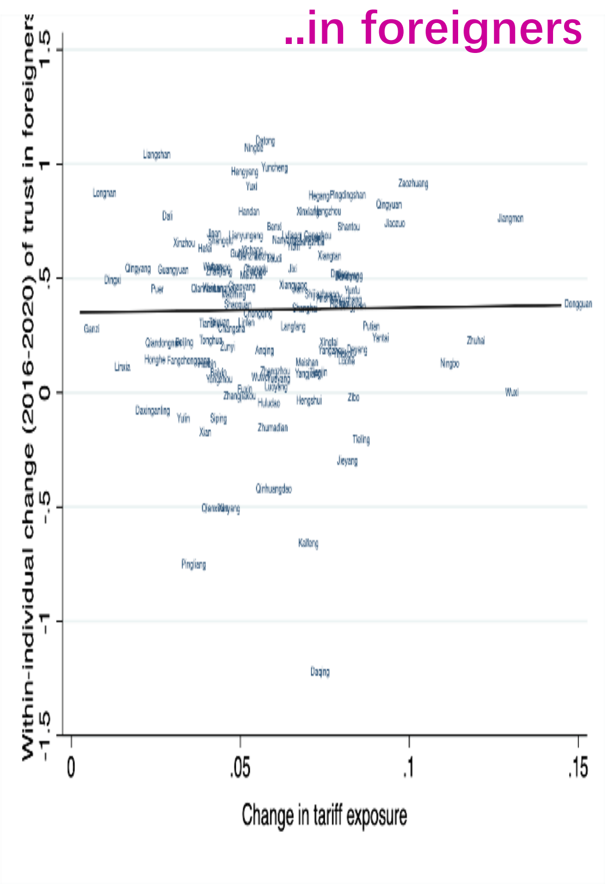
Part 4: Evidence from Household Surveys

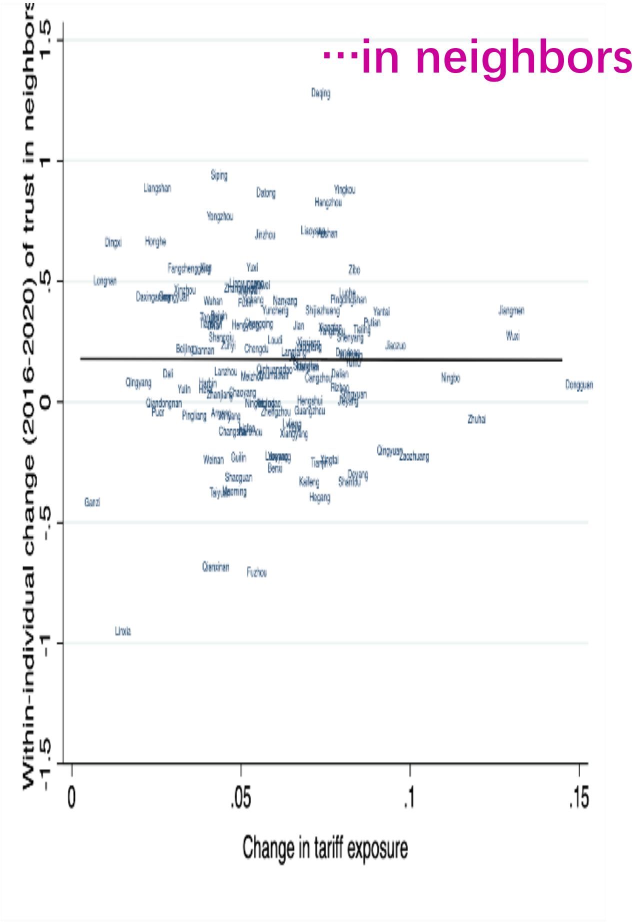
China Family Panel Surveys

- nationwide, longitudinal survey launched by Peking University
- conducted every two years over 2010-2020.
- covers 122 cities and contains a panel structure at the individual respondent level.
- A module to elicit respondents' trust level.
    - "On a scale of 1 (least trust) to 10 (most trust), how much do you trust **Americans** (or your parents, your neighbors, strangers, local government leaders, doctors)?

Change in trust in X from 2016 to 2020







The vertical axis is the city-level average within-individual change in trust in certain group of people between 2016 and 2020. The horizontal axis is change in tariff exposure between 2016 and 2020.

Decline in trust in Americans in CFPS surveys from 2016-2020

- Dependent variable: within-individual change in trust in certain group of people between 2016 and 2020.
- RHS variable: change in the city-level tariff exposure between 2016 and 2020.
- Standard errors are clustered at the city-level.

Trust in	(1) Americans	(2) Parents	(3) Neighbors	(4) Foreigners	(5) Leaders	(6) Doctors
$\widetilde{\Delta}$ tariff exposure	**-5.65*** **	1.470*	-1.113	-1.094	-1.464	0.246
	(1.42)	(0.848)	(1.380)	(1.345)	(1.731)	(1.391)
N	11762	11938	12070	12007	11993	12069
R-sq	0.003	0.000	0.000	0.000	0.000	0.000

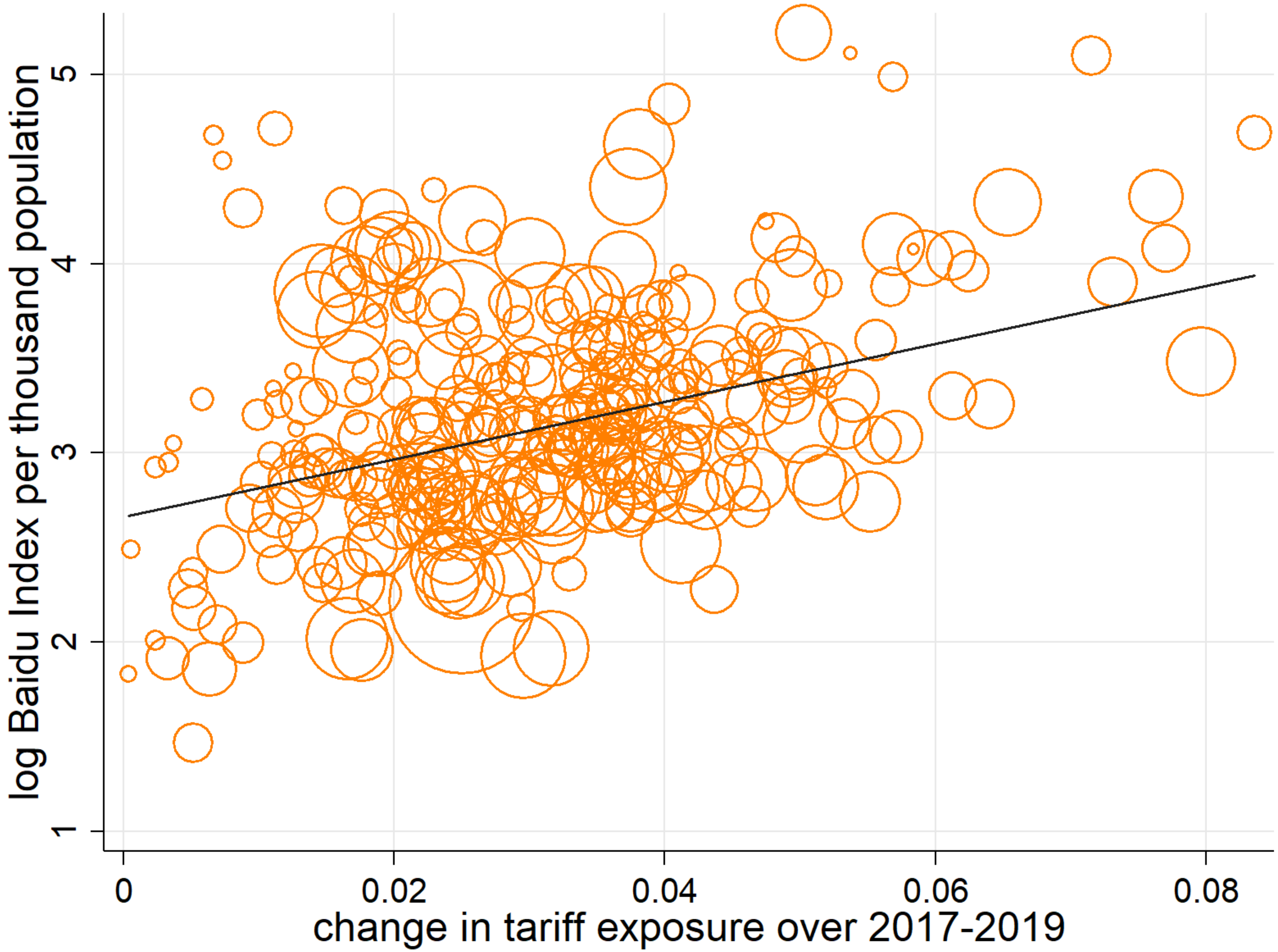
Trust in	(1) **Americans**	(2) Parents	(3) Neighbors	(4) Foreigners	(5) Leaders	(6) Doctors
tariff exposure	**-4.09** **	0.812	-1.447	-0.240	0.111	0.124
	(1.76)	(0.924)	(1.356)	(1.277)	(1.792)	(1.803)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	53161	54033	54341	54158	54085	54317
R-sq	0.631	0.593	0.636	0.630	0.662	0.643

Part 5: Complementary Evidence from Baidu Searches

awareness of /concern for trade wars

search for US vs. non-US movies

search for tourist destinations /sports shoes/ colleges



Tariff exposure and Baidu Index for "US-China Trade War"

Notes: The figure presents a scatter plot between the cumulative Baidu Index over 2017-2019 per thousand population and change in tariff exposure over the same period. The composite index is constructed from aggregating the Baidu Index for the three trade-war-related keywords. The size of each bubble corresponds to city population in 2017.

Table 10: Effects on the Baidu Index for Trade War or Trade Frictions

Keyword	(1) Sino-US trade war	(2) Trade war	(3) Sino-US trade friction	(4) Composite index
A. Long Difference				
		Δ log (1+Baidu Index)		
Δ tariff exposure	41.378***	38.343***	24.340***	30.321***
	(4.886)	(4.831)	(4.079)	(4.775)
Δ log GDP pc	1.271	0.452	0.897	1.064
	(0.940)	(0.919)	(0.630)	(0.858)
R-square	0.171	0.170	0.102	0.124
N obs	325	325	325	325
B. Panel Regressions				
		log (1+Baidu Index)		
tariff exposure	8.478***	8.580***	5.338**	9.346***
	(2.664)	(2.685)	(2.203)	(2.697)
log GDP pc	0.151	0.138	0.181	0.164
	(0.233)	(0.230)	(0.199)	(0.270)
R-square	0.900	0.904	0.818	0.910
city FE	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes
N obs	7800	7800	7800	7800

Notes: Baidu Index measures the number of searches on Baidu.com using relevant terms. The composite index for trade war is constructed by aggregating the Baidu Index for the three trade-war-related keywords. Month FE refers to fixed effects for specific months (e.g., 2018 July) instead of months of the year. Robust standard errors are presented in Panel A. Standard errors in Panel B are clustered by city and region-month. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 11: Baidu Index for Movies

Keyword	(1) US movies	(2) Top 5 US movie titles	(3) Foreign movies	(4) Movie tickets
A. Long Difference				
	Δ log (1+Baidu Index)			
Δ tariff exposure	-6.114***	-3.371***	2.060	-1.259
	(1.389)	(0.995)	(2.129)	(1.916)
Δ log GDP pc	0.261	0.468***	1.106***	0.611***
	(0.177)	(0.162)	(0.288)	(0.219)
R-square	0.104	0.109	0.048	0.022
N obs	325	325	325	325
B. Panel Regressions				
	log (1+Baidu Index)			
tariff exposure	-2.646***	-3.172	-0.414	0.387
	(0.587)	(2.041)	(0.622)	(0.701)
log GDP pc	0.161	0.109	0.153*	0.066
	(0.117)	(0.102)	(0.090)	(0.115)
R-square	0.924	0.969	0.788	0.941
city FE	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes
N obs	7800	7800	7800	7800

Notes: Baidu Index measures the number of searches on Baidu.com using relevant terms. Month FE refers to fixed effects for specific months (e.g., 2018 July) instead of months of the year. Robust standard errors are presented in Panel A. Standard errors in Panel B are clustered by city and region-month. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 12: Baidu Index for Tourism

	(1)	(2)	(3)	(4)
Keyword	US tourism	US visa for tourists	Japanese tourism	Tourism
A. Long Difference				
		Δ log (1+Baidu Index)		
Δ tariff exposure	-4.653*	-6.395***	-2.082	-2.107*
	(2.456)	(1.972)	(1.402)	(1.189)
Δ log GDP pc	-0.188	0.347	0.230	0.523***
	(0.308)	(0.271)	(0.180)	(0.160)
R-square	0.011	0.042	0.016	0.071
N obs	325	325	325	325
B. Panel Regressions				
		log (1+Baidu Index)		
tariff exposure	-5.866***	-5.685***	-1.580	0.582
	(0.735)	(0.981)	(0.980)	(0.510)
log GDP pc	-0.300**	0.032	-0.112	0.126
	(0.127)	(0.161)	(0.125)	(0.077)
R-square	0.835	0.874	0.913	0.965
city FE	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes
N obs	7800	7800	7800	7800

Notes: Baidu Index measures the number of searches on Baidu.com using relevant terms. Month FE refers to fixed effects for specific months (e.g., 2018 July) instead of months of the year. Robust standard errors are presented in Panel A. Standard errors in Panel B are clustered by city and region-month. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 14: Baidu Index for Studying Abroad

	(1)	(2)	(3)	(4)
Keyword	US college	UK college	Japanese college	Study abroad
A. Long Difference				
		Δ log (1+Baidu Index)		
Δ tariff exposure	-2.677	0.213	-0.177	1.459
	(2.249)	(1.710)	(1.695)	(1.973)
Δ log GDP pc	0.676**	0.309	0.703***	-0.011
	(0.272)	(0.259)	(0.222)	(0.288)
R-square	0.031	0.005	0.028	0.002
N obs	325	325	325	325
B. Panel Regressions				
		log (1+Baidu Index)		
tariff exposure	**-1.464***	**-0.401**	**0.103**	**0.827**
	(0.824)	**(0.687)**	**(0.642)**	**(1.247)**
log GDP pc	0.341**	-0.021	0.120	0.136
	(0.152)	(0.127)	(0.136)	(0.192)
R-square	0.866	0.880	0.872	0.856
city FE	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes
N obs	7800	7800	7800	7800

Notes: Baidu Index measures the number of searches on Baidu.com using relevant terms. Month FE refers to fixed effects for specific months (e.g., 2018 July) instead of months of the year. Robust standard errors are presented in Panel A. Standard errors in Panel B are clustered by city and region-month. ***p < 0.01, **p < 0.05, *p < 0.1.

Part 5: Extensions

- different movie genres
  - salience of “Americanism” could differ
- different types of theaters
  - more affluent audience may use fancier theaters
- different showing times
  - different times catering to different demographics
- persistence of the effect
  - Does the effect persist to 2021?

Table 15: Different Movie Genres

	(1)	(2)	(3)	(4)	(5)
Genre	Action	Drama	Sci-fi/ fantasy	Animation	others
% of total revenue	65.5%	5.3%	13.7%	10.7%	4.8%
A. $\tilde{\Delta}$ log movie revenue					
$\tilde{\Delta}$ tariff exposure	-2.624***	-5.051	0.103	2.557*	2.967
	(0.977)	(4.504)	(2.279)	(1.395)	(2.133)
Theater FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
N cities	325	324	325	325	325
N theaters	9968	8248	9448	9673	9034
N obs	176964	45795	71239	126971	62422
B. $\tilde{\Delta}$ share of total theater revenue					
$\tilde{\Delta}$ tariff exposure	-0.464*	-0.094**	-0.177	-0.039	-0.043
	(0.255)	(0.047)	(0.125)	(0.038)	(0.056)
Theater FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
N cities	325	325	325	325	325
N theaters	10057	10057	10057	10057	10057
N obs	202046	202046	202046	202046	202046

Notes: All regressions include month and theater fixed effects, and baseline city controls. Month FE refers to fixed effects for specific months (e.g., 2018 July) instead of the months of the year. Standard errors in parentheses are clustered by city and region-month. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 17: Local Newspaper Coverage

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	$\tilde{\Delta}$ log (1+N articles)		$\tilde{\Delta}$ log US movie revenue			
$\tilde{\Delta}$ tariff exposure	-0.202	-1.123	-1.702**	-2.679***	-1.830**	-2.807***
	(0.447)	(1.088)	(0.710)	(0.724)	(0.719)	(0.734)
$\tilde{\Delta}$ log (1+N articles)			0.001	0.007	0.022	0.035
			(0.012)	(0.014)	(0.021)	(0.023)
$\tilde{\Delta}$ tariff exposure ×					-0.915	-1.259*
… $\tilde{\Delta}$ log (1+N articles)					(0.630)	(0.697)
City FE	No	Yes	No	No	No	No
Theater FE	No	No	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N cities	187	187	187	325	187	325
N theaters			7879	9983	7879	9983
Sample	restricted	restricted	restricted	full	restricted	full
N obs	4488	4488	156248	197715	156248	197715

Notes: "N articles" refers to the number of articles that contains "Sino-US trade war" and "Sino-US trade frictions" in titles published by the local newspapers. The restricted sample includes only cities with at least one daily newspaper appeared in the WiseNews database while the full sample includes all cities from the baseline. All regressions include month FE and baseline city controls. Month FE refers to fixed effects for specific months (e.g., 2018 July) instead of months of the year. Standard errors in parentheses are clustered by city and region-month. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 18: Long-term Effects of the Trade War, 2017-2021

	(1)	(2)	(3)	(4)
	US movies		All movies	
A. City level				
Change in tariff exposure	-1.247	-1.787*	-0.590	-1.035
	(1.041)	(1.010)	(0.888)	(0.868)
Covid-19: 1 to 10 cases		-0.289**		-0.445***
		(0.138)		(0.134)
Covid-19: more than 10		-1.333***		-0.949***
		(0.409)		(0.178)
R-square	0.766	0.780	0.562	0.591
Month FE	Yes	Yes	Yes	Yes
N obs	3829	3829	3874	3874
B. Theater level				
Change in tariff exposure	-2.262**	-2.625***	0.035	-0.653
	(1.003)	(0.936)	(0.606)	(0.596)
Covid-19: 1 to 10 cases		-0.073		-0.162**
		(0.106)		(0.080)
Covid-19: more than 10		-0.412**		-0.714***
		(0.160)		(0.160)
R-square	0.556	0.558	0.311	0.323
Month FE	Yes	Yes	Yes	Yes
N obs	69950	69950	77274	77274

Notes: This table presents regression results based on long differences between 2017 and 2021. The LHS variable is change in log monthly movie revenue from 2021, relative to the same month in 2017. All regressions include changes in log GDP per capita, initial GDP per capita and month fixed effects. The omitted category of covid-19 severity is “0 case.” Standard errors in parentheses are clustered by city and region-month. ***p < 0.01, **p < 0.05, *p < 0.1.

Conclusion

The US trade war under Trump

- appears to reduce Chinese appetite for US movies, cars, and colleges
- not explained by an income effect or a government effect
- Consistent with a view that US tariff increases not perceived as just or legitimate
- Consistent with the WTO ruling
- Heterogeneity for more affluent people
- Trade war hurts the US soft power


thank you