

Trade Part: Lecture 8

Modern Empirical Method I: Dynamic Difference-in-Difference

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Motivation

- Protectionism has been rising in the last decade
 - A common way is to impose tariffs on imported goods (import tax)
- Rich administrative data are increasingly becoming available to researchers
 - For trade economics, customs data are one of the most important ones
- We extend the difference-in-difference (DiD) framework to a dynamic one
 - Often called dynamic DiD or event-study regressions
 - Apply it to the analysis of tariff escalation
- The dynamic DiD has become increasingly popular in the last decade
 - A handy way to communicate complex econometrics, even to non-economists

Idea of the dynamic DiD regression

- The simple DiD model was:

$$y_{it} = \alpha + \beta \text{Treat}_i + \gamma \text{Post}_t + \delta^{DiD} (\text{Treat}_i \times \text{Post}_t) + \epsilon_{it} \quad (1)$$

- The dynamic DiD regression is:

$$y_{it} = \beta_i + \gamma_t + \sum_{\tau=\underline{\tau}}^{\bar{\tau}} \delta_{\tau}^{DDiD} (\text{Treat}_i \times \mathbf{1}\{E_i = t - \tau\}) + \epsilon_{it} \quad (2)$$

E_i : the treatment event date (0 for the controls)

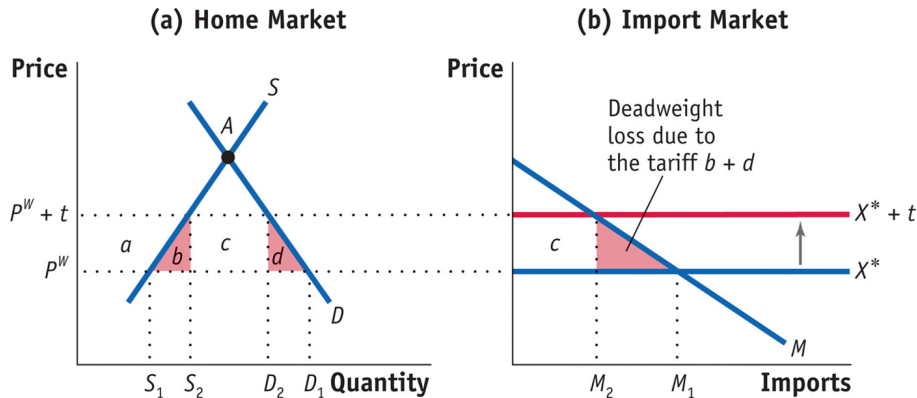
- This extension gives a simple and intuitive coefficient visualization
- However, we have to be careful about the construction of control groups

The analysis of Trump Tariff - Fajgelbaum et al. (2020)

Background

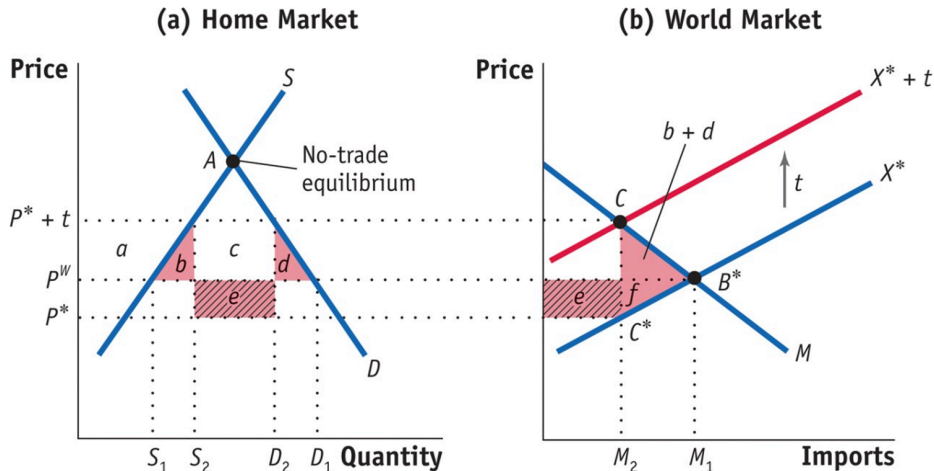
- In 2018, the U.S. raised tariffs on 12.7% of its imports.
 - Average tariff increased from 2.6% to 16.6%.
 - Trade partners retaliated by raising tariffs on 8.2% of U.S. exports.
 - We won't carefully study this today, but it is an interesting topic in the paper
- Largest return to protectionism since the 1930 Smoot-Hawley (SH).
 - The SH is the U.S. Act imposing one of the largest tariffs in the U.S. history
- The welfare effect depends on the tariff incidence
 - The key mechanism is the **terms-of-trade effect**
 - I.e., import price reduction that raises the gain from tariff revenue
 - This can be understood in a partial equilibrium diagram, up next

Review of Undergrad Trade: Tariffs under small-open economy



Source: Feenstra and Taylor "International Trade" 4th Ed. Figure 8-5

Review of Undergrad Trade: Tariffs under large-open economy



Source: Feenstra and Taylor "International Trade" 4th Ed. Figure 8-9

- What were the effects on trade volumes and prices?
 - Dynamic DiD shows up as a natural way to approach the question
- Not today but in the paper:
 - Use tariffs to identify import demand and export supply elasticities.
 - Use them to answer the aggregate and regional impacts on the U.S. economy in a general equilibrium (GE) model

- All data frequency is monthly
- Sources:
 - U.S. statutory import tariffs from the U.S. International Trade Commission (USITC)
 - Retaliatory tariffs on U.S. exports from foreign official documents
 - Publicly available (!) trade data from U.S. Census Bureau
- The trade data contain:
 - values and quantities, so can construct **unit values** (=value/quantity)
 - all countries i and HS-10 product g , refer to the (i, g) pair as “variety”
 - Period: 2017:1 to 2019:4

Summary Statistics: U.S. Tariffs

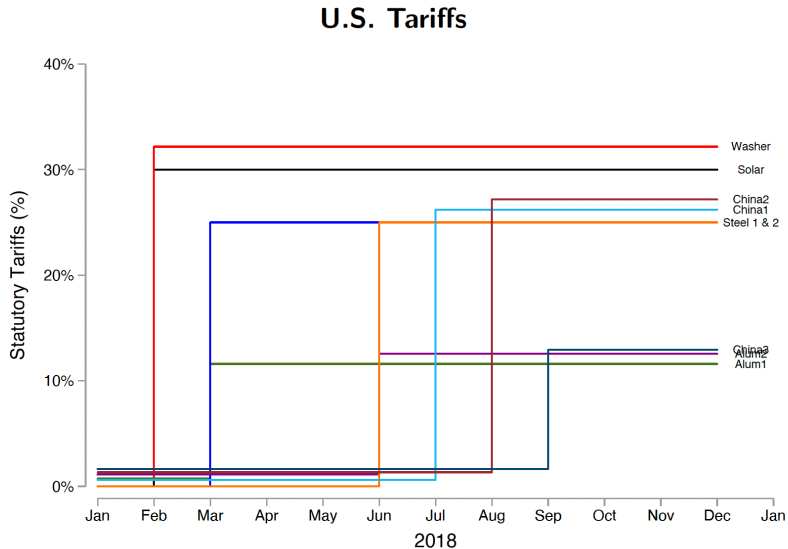
Panel A: Tariffs on U.S. Imports Enacted by U.S. in 2018

Tariff Wave	Date Enacted	Products	2017 Imports		Tariff (%)	
		(# HS-10)	(mil USD)	(%)*	2017	2018
Solar Panels	Feb 7, 2018	8	5,782	0.2	0.0	30.0
Washing Machines	Feb 7, 2018	8	2,105	0.1	1.3	32.2
Aluminum	Mar-Jun, 2018	67	17,685	0.7	2.0	12.0
Iron and Steel	Mar-Jun, 2018	753	30,523	1.3	0.0	25.0
China 1	Jul 6, 2018	1,672	33,510	1.4	1.3	26.2
China 2	Aug 23, 2018	433	14,101	0.6	2.7	27.0
China 3	Sep 24, 2018	9,102	199,264	8.3	3.3	12.9
Total		12,043	302,970	12.7	2.6	16.6

Summary Statistics: Retaliatory Tariffs

Panel B: Retaliatory Tariffs on U.S. Exports Enacted by Trading Partners in 2018

Retaliating Country	Date Enacted	Products	2017 Exports		Tariff (%)	
		(# HS-10)	(mil USD)	(%)*	2017	2018
China	Apr-Sep, 2018	7,474	92,518	6.0	8.4	18.9
Mexico	Jun 5, 2018	232	6,746	0.4	9.6	28.0
Turkey	Jun 21, 2018	244	1,554	0.1	9.7	31.8
European Union	Jun 22, 2018	303	8,244	0.5	3.9	29.2
Canada	Jul 1, 2018	325	17,818	1.2	2.1	20.2
Russia	Aug 6, 2018	163	268	0.0	5.2	36.8
Total		8,073	127,149	8.2	7.3	20.4



The key feature of the timeline

- The timing of the tariff rise (called the “event” later) is **staggered**
 - I.e., Some rise early; others rise late
 - During the sample period, the tariffs were never lifted.
- This is a common feature of many policy changes
 - Policies are often implemented in specific units (goods/states) first,
 - and then are extended to other units
- This generates a natural identifying variation
 - I.e., Compared to those changing later, how much do those changing earlier respond earlier?
- The level of the hike is also heterogeneous across goods
 - Not utilized today; analyzed in the paper

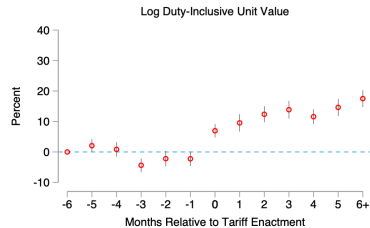
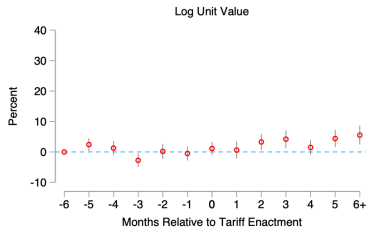
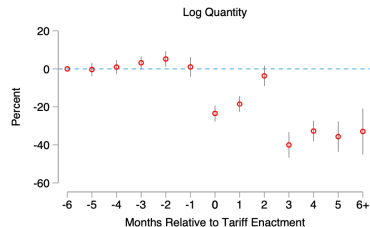
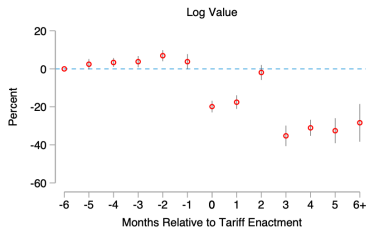
Dynamic DiD specification

- Notation:
 - i : import source country, g : product (HS-6), t : month
 - target_{ig} : the tariff target indicator for i, g
 - e_{igt} : “Event time” i.e., # of months after t since (i, g) is targeted
- Compared trends of targeted varieties relative to non-targeted varieties:

$$\ln y_{igt} = \alpha_{ig} + \alpha_{gt} + \alpha_{it} + \sum_{j=-6}^6 \beta_{0j} I(e_{igt} = j) + \sum_{j=-6}^6 \beta_{1j} I(e_{igt} = j) \times \text{target}_{ig} + \epsilon_{igt}$$

- variety (α_{ig}), product-time (α_{gt}), country-time (α_{it})
- Inclusion of α_{gt} guarantees that the identification comes from a comparison of source countries conditional on product-month
- Standard error clustering: Country, HS-8 products

Event Study Diagrams: Plot of β_{1j} 's



The parallel-trend assumption

- Again, for causality, we need parallel trend (PT) assumptions
 - I.e., Targeted varieties would have had similar import trends as non-targeted ones had they not been targeted
 - This may be justified by the unprecedented policy scale under the Trump administration
 - However, again, this assumption is not directly testable
- The role of **pre-trend analysis** in the dynamic DiD:
 - NB: we have included negative event dates
 - This allows us to compare the trends before the events between targeted and non-targeted varieties
 - This serves as natural supportive evidence of the parallel trend

Takeaway and interpretation

- Under the PT assumption, the Trump tariff:
 - reduced the US import by value and quantity by 33%,
 - did not affect unit values strongly,
 - and thus, increased the duty-inclusive unit values
- This means that the export supply curve to the US is likely elastic
 - Otherwise, we would have observed the reduction in the unit values without duty
- This suggests that the US welfare decreased due to the consumer welfare loss

(Sidestep, if time allows:) On the small-open assumption

- But, be careful about interpreting this as the US being small
- Rather, before-duty price reduction can appear in control groups too, nullifying the coefficients (Bagwell Staiger, '99)
 - This happens when, e.g., wages adjust and are reflected in the production cost for all goods
- Cf. **Stable Unit Treatment Values (SUTVA)** assumption in the potential outcome framework
 - SUTVA means that the control group is not affected by the intervention on the treatment group
 - I.e., Fajgelbaum et al. (2019) admits the potential violation of SUTVA

Other Results not Covered in the Lecture

- GE exercise
 - Consumer loss amounted to -0.27% of GDP.
 - Aggregate effect: -0.04% of GDP.
- Regional analysis
 - Higher import protection in electorally competitive counties.
 - Republican counties were most negatively affected due to retaliation.

General considerations when using dynamic DiD

- Many empirical applications of dynamic DiD concern staggered treatment.
- Staggered treatment is when units enter into treatment at different periods;
 - but then they do not ever switch out of treatment.
- A burgeoning literature analyzes (Goodman-Bacon '21; Callaway Sant'anna '21, CSA):
 - what an empirical researcher should be careful about, and
 - what a common estimation method (e.g., dynamic DiD) actually estimates
- Disclaimer: my approach to this topic in this lecture is partial
 - Full discussion will be notation-heavy and too much of econometric details
 - So, I will focus on a high-level summary of the potential problem and remedies

Building blocks: simple 2×2 DiD

- The literature has a consensus that the dynamic DiD estimates under staggered treatment should be decomposed into “simple DiDs”
- I.e., Compare two groups A and B , differing in terms of event time
 - Suppose A is treated later, and B is earlier
- Two “pre and post” periods
 - E.g., A is “pre” (not yet treated), while B is treated in the later period
- Then the simple 2×2 DiD is

$$\hat{\delta}_{pre,post}^{AB} = (\bar{y}_{B,post} - \bar{y}_{B,pre}) - (\bar{y}_{A,post} - \bar{y}_{A,pre}) \quad (3)$$

The negative weight problem

- Many authors provide the weighted average formulation of (2) that

$$\hat{\delta}_{\tau}^{DDiD} = \sum_{A,B,pre,post} w_{\tau}(A, B, pre, post) \hat{\delta}_{pre,post}^{AB} \quad (4)$$

where $w_{\tau}(A, B, pre, post)$ is the weight to summarize simple DiDs

- However, careless regression of the form (2) leads the **negative weight problem** (De Chaisemartin and D'Haultfœuille, 2020, DD)
- Simple example by DD: Suppose the observed treatment dynamics are

Group	$t = 1$	$t = 2$	$t = 3$
A	No	No	Yes
B	No	Yes	Yes

The negative weight problem (Cont'd)

- In this case, the regression would aggregate the two DiD estimates
 1. $(\bar{y}_{B2} - \bar{y}_{B1}) - (\bar{y}_{A2} - \bar{y}_{A1})$: This is fine; follows the simple DiD structure in (3)
 2. $(\bar{y}_{A3} - \bar{y}_{A2}) - (\bar{y}_{B3} - \bar{y}_{B2})$: Is this fine?
- In the second DiD, regression (2) thinks that group B is “control”:
 - ...because the treatment status, “yes”, does not change between $t = 2$ and 3
- The second estimate is not necessarily valid:
 - ...when the treatment effect is dynamic, and group B receives effects in $t = 3$
- Mathematically, this implies that the weight $w_\tau(\cdot)$ in (4) can be negative
 - This is problematic: $\hat{\delta}_\tau^{DDiD}$ can be negative even if all simple DiDs are positive!
 - In this sense, $\hat{\delta}_\tau^{DDiD}$ is hard to interpret

A remedy

- To avoid this complication, we have to give up a “kitchen-sink” regression (2)
- All identification assumptions depend on the construction of control groups
- Specifically, CSA propose the following two control group setups
 - **Not-yet-treated groups**: Only include units that are not yet treated (but will be) as the control
 - Less concern of apple-to-orange comparison, more concern of anticipation effect
 - **Never treated groups**: Only include units that are never treated (to the future) as the control
 - The flipside of the pros and cons above
- NB: Both assumptions exclude already treated units from the control group
 - This avoids the negative weight problem

Different approaches to estimating the simple DiDs

CSA also propose the following three estimation methods to recover the simple

1. Outcome regressions: Regress the simple 2×2 DiD models (cf. eq. 1)
2. Inverse propensity-score weighting (IPW):
 - Take the weighted average of the difference b/w treated and control units
 - The weight is the IPW, the estimated probability of entering into treatment
3. “Doubly robust” estimator: Use IPW to weight the outcome regression
 - This is CSA’s preferred method

Further readings

- This slide is not for the exam but for those applying DDiD in the project
- Miller (2023) summarizes a “hitchhiker’s guide,” which includes discussions on further practical considerations:
 - Recommendation of plotting the raw trends for both the treatment and control (Recall DiD figure from Lecture 7)
 - Choice between not-yet-treated and never-treated as the control
 - Choice of the period window, $\underline{\tau}$ and $\bar{\tau}$
 - Whether to control the unit-specific trends
 - How to compute the cluster-robust standard error
 - How to handle more-than-one-event within a unit
 - and more...