# Propagating Trade Protectionism

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## Motivation

### Summary

This paper studies the importance of global supply chains for the **propagation of trade policy shocks**. Protectionist measures recently adopted by the U.S. had adverse economic consequences for industries throughout the world, including in particular targeted industries, but also domestic industries as well as third parties uninvolved in the trade conflicts. Global supply chain linkages between industries explain the propagation of concentrated trade actions. They reinforce the **direct effects** on targeted industries and give rise to **spillover effects** that are negative and larger than direct effects. These findings suggest that **global supply chains raise the economic costs of interventionist trade policy.**

### Recent U.S. Trade Protectionism as a Laboratory

U.S. trade policy fundamentally changed in 2018:

- after decades of continuously lowering trade barriers, the U.S. adopted protectionist measures
- this decision was made in an economic environment characterized by globalization: industries around the world are connected by global supply chains

→ such economic dependencies potentially work as a propagation mechanism for otherwise concentrated trade policy shocks

**Research question:** How do trade policy shocks affect industries throughout the world? To what extent are trade policy shocks transmitted through global supply chain linkages between industries?

**Results:**

1. 2018 U.S. trade actions had negative economic consequences for industries around the world, including targeted industries, as intended, but also domestic industries, which were meant to be protected by the tariffs, and third party industries, which were uninvolved in the trade conflicts
2. global supply chain linkages between industries explain the propagation of trade policy shocks: they reinforce the direct effects on targeted industries and give rise to spillover effects that are negative and larger than direct effects

⇒ **global supply chains raise the economic costs of interventionist trade policy**

⇒ **traditional view of duties as detrimental to targeted industries and beneficial to protected industries is too simple in a globalized world economy**

#### 2018 U.S. Trade Actions: A Chronicle

| Date | Wave | Type | Targets: Countries | Targets: #ISIC Sectors |
|---|---|---|---|---|
| Jan 23, 2018 | Solar panels & washers | Proclamation | All except Brazil, India, Indonesia, Turkey | 2 |
| Feb 7, 2018 | Solar panels & washers | Effect | All except Brazil, India, Indonesia, Turkey | 2 |
| Mar 8, 2018 | Aluminum & steel | Proclamation | All except Canada, Mexico | 5 |
| Mar 22, 2018 | Aluminum & steel | Proclamation | All except Australia, Brazil, Canada, EU, Mexico, South Korea | 5 |
| Apr 3, 2018 | China 1 & 2 | Proposed list | China | 16 |
| Apr 30, 2018 | Aluminum | Proclamation | South Korea | 4 |
| May 31, 2018 | Aluminum & steel | Proclamation | Brazil, Canada, EU, Mexico | 5 |
| Jun 15, 2018 | China 1 & 2 | Updated list | China | 15 |
| Jul 10, 2018 | China 3 | Proposed list | China | 23 |
| Aug 7, 2018 | China 2 | Updated list | China | 13 |
| Aug 10, 2018 | Steel | Proclamation | Turkey | 5 |
| Aug 23, 2018 | China 2 | Effect | China | 13 |
| Sep 17, 2018 | China 3 | Updated list | China | 23 |
| Sep 24, 2018 | China 3 | Effect | China | 23 |

### Measuring Stock Price Responses

I measure stock price reactions in an event study to quantify the economic effects of the 2018 U.S. trade actions. In a first step, I determine how quickly stock prices incorporate trade policy news by examining average value-weighted stock returns of industries in business weeks surrounding the events

$$R_{i,d} = \alpha + \sum_{\tau=-2}^{+2} \beta_\tau \, event\ time(\tau)_d + \mu_i + \varepsilon_{i,d}, \tag{1}$$

where $d$ are all trading days within the sample period. $event\ time(\tau)_d$ is a dummy variable that takes on value 1 if date $d$ is $\tau$ trading days away from the nearest event. The specification compares daily logarithmic excess returns $R_{i,d}$ on event days with those on non-event days, captured by the constant $\alpha$, and controls for time-invariant characteristics $\mu_i$ of industry $i = 1, \dots, N$ through fixed effects. Based on the estimated $\hat{\beta}_\tau$, I choose an appropriate **event window** over which the most part of the stock market reaction takes place.

In a next step, I follow standard event study methodology (MacKinlay, 1997) and calculate **cumulative returns** over event windows $\tau^*$ surrounding event dates $t$ as

$$CR_{i,t} = \sum_{\tau^*} R_{i,t+\tau^*}. \tag{2}$$

## Empirical Strategy

### Identification

**Key identifying assumptions:**

1. no news other than the trade action moved stock prices over the course of the event window
   - → choosing an event window as short as possible greatly reduces the likelihood that omitted variables distort the measurement
   - → any potentially omitted shock was likely dominated by the news of U.S. trade actions because the U.S. is the largest economy in the world and its measures, in particular those against China, were unprecedented in scope (Bown, 2019)
   - trade actions might have been influenced by firm characteristics that also explain stock returns
   - → include fixed effects that absorb industry characteristics that do not vary across events
2. no simultaneous causality: trade actions are not influenced by cumulative returns
   - three different types of trade actions: publication dates of presidential proclamations and USTR tariff lists as well as effective dates
   - → proclamations and tariff lists are prepared well in advance of their publication because they require investigations, negotiations, or interagency cooperation
   - → effective dates are set in advance in order to allow U.S. Customs and Border Protection to prepare for collecting the duties

### Modeling Propagation

The baseline model, referred to as the **OLS model**, reads as

$$CR_{i,t} = \beta \, target_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \tag{3}$$

where $target_{i,t}$ is a dummy variable that takes on value 1 if at least one of industry $i$'s products was targeted at event $t$. $\mu_i$ and $\lambda_t$ denote industry and event fixed effects, respectively.

The OLS model, which sets spillover effects to zero by construction, can be generalized to account for spatial dependence. The most general model considered here is the **spatial Durbin model (SDM)**

$$CR_{i,t} = \beta \, target_{i,t} + \theta \sum_{j=1}^{N} W_{i,j} target_{j,t} + \rho \sum_{j=1}^{N} W_{i,j} CR_{j,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \tag{4}$$

where $W_{i,j}$ denotes an element of the $N \times N$ spatial weights matrix $W$ and represents the strength of the input-output relation between two industries $i$ and $j$. $W$ is based on dollar values of trade flows; its diagonal elements are set to zero and the elements of each row are normalized to sum to unity. The SDM models includes a spatial lag of the *independent* variable, $\sum_{j=1}^{N} W_{i,j} target_{j,t}$, as well as a spatial lag of the *dependent* variable, $\sum_{j=1}^{N} W_{i,j} CR_{j,t}$. It therefore allows two types of spatial spillover effects, exogenous through $\theta$ and endogenous through $\rho$.

The SDM model reduces to the so-called **SLX model** for $\rho = 0$ and to the **spatial autoregressive model (SAR)** for $\theta = 0$. The key difference is that, in the SLX model, the cumulative return of industry $i$ depends on the *target*-statuses of all other industries, while in the SAR model, it depends on the cumulative returns of all other industries. The SAR model is often interpreted as a representation of an equilibrium process, in which the dependent variables of different cross-sectional units are jointly determined (Elhorst, 2014). In the given context, the SAR model can reflect that investors jointly reconsider the stock market valuations of all firms following a trade action.

$\beta$, $\theta$, and $\rho$, together with $W$, determine the magnitudes of **direct and spillover effects**. Direct effects are defined as the average of own partial derivatives $\partial CR_{i,t} / \partial target_{i,t} \; \forall \; i$ and spillover effects as the sum of cross partial derivatives $\partial CR_{i,t} / \partial target_{j,t} \; \forall \; i \neq j$ (LeSage and Pace, 2009).

### Data

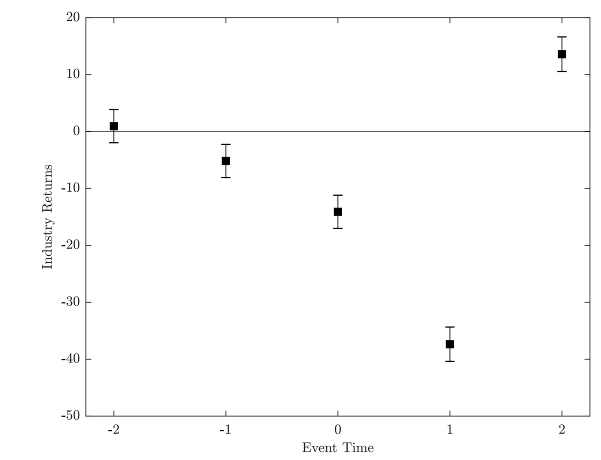
- global supply chains: $W$ is based on global inter-industry trade flows of goods and services collected from the 2014 world input-output table
- stocks: daily returns and industry affiliations from CRSP and CRSP/COMPUSTAT Merged for the U.S., Thomson Reuters Datastream and Worldscope for all other countries; aggregated to industries using market capitalization-weights
- targeted products: HTS product codes from presidential proclamations in the Federal Register and from tariff lists as made public by the Office of the USTR; mapped to ISIC sectors based on Pierce and Schott (2012)

→ 8,512 industry-event observations representing 608 unique industries, 50 ISIC sectors, and 28 countries across 14 U.S. trade actions undertaken between Jan 23, 2018 and Sep 24, 2018

## Results

### Stock Prices Respond Quickly

#### Stock Returns Around Trade Actions




- greatest part of stock markets' reactions takes place on the event day and the following day ($\hat{\beta}_0$=−14 bps, $\hat{\beta}_1$=−37 bps)

→ construct event windows $\tau^*$ of two (0 to +1) trading days

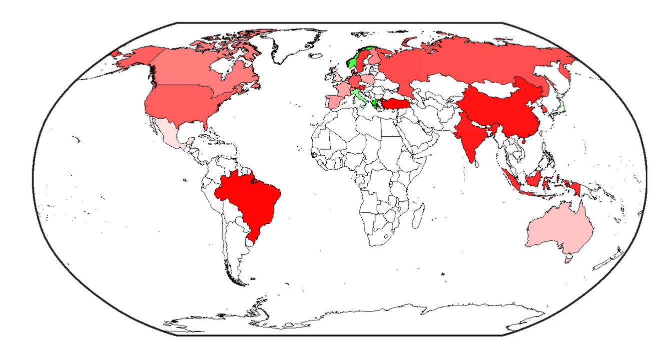
- normal returns are negligible over short periods ($\hat{\alpha}$=1 bp)

→ compute cumulative returns in Equation (2) without subtracting normal returns

⇒ **trade policy shocks have negative aggregate effects**

### Industries Around the World React Differently

#### Market Responses Around the World



- average stock market reaction is negative in almost every country
- Asia-Pacific region is severely hit, in particular China (−91 bps)
- impact on Europe is moderate
- U.S. ranks in the middle (−47 bps)

→ **trade policy shocks have different effects on industries across countries**

#### Targeted vs. Protected vs. Third Parties

| | $CR_{i,t}$ (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $target_{i,t}$ | −93.83*** | −83.03*** | −83.12*** | −78.72*** |
| | (−5.47) | (−5.26) | (−5.28) | (−4.27) |
| $US_{i,t}$ | −46.87*** | 1.00 | | |
| | (−4.22) | (0.10) | | |
| $third\ party_{i,t}$ | −49.24*** | | | |
| | (−14.88) | | | |
| Event FE | No | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |
| Observations | 8512 | 8512 | 8512 | 8512 |
| $R^2$ | 0.031 | 0.197 | 0.197 | 0.291 |

- targeted industries lose −94 bps, U.S. industries −47 bps, third parties −49 bps

→ even third parties that are not *directly* affected by trade actions lose value

→ **targeted industries perform significantly worse** than third parties (−83 bps); U.S. industries do not perform better or worse

### Propagation Through Global Supply Chains Matters

#### Spatial Panel Models I

| Panel A: Estimates | $CR_t$ (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $target_t$ | −33.39* | −36.10*** | −38.90*** | −13.83 | −38.07*** | −27.42* |
| | (−1.76) | (−3.15) | (−2.81) | (−0.66) | (−2.81) | (−1.71) |
| $W \times target_t$ | −152.18*** | | 8.72 | −246.13*** | | −40.20 |
| | (−4.65) | | (0.37) | (−5.82) | | (−1.24) |
| $W \times CR_t$ | | 0.88*** | 0.88*** | | 0.88*** | 0.89*** |
| | | (98.07) | (109.27) | | (107.22) | (108.28) |
| Event FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes | Yes | Yes |
| Observations | 8512 | 8512 | 8512 | 8512 | 8512 | 8512 |
| $R^2$ | 0.199 | 0.576 | 0.577 | 0.294 | 0.618 | 0.619 |
| **Panel B: Marginal Effects** | | | | | | |
| Direct Effects | | | | | | |
| $target_t$ | −33.39* | −38.56*** | −41.59*** | −13.83 | −41.44*** | −34.17** |
| | (−1.76) | (−3.19) | (−2.98) | (−0.66) | (−2.80) | (−2.17) |
| Spillover Effects | | | | | | |
| $target_t$ | −152.18*** | −265.84*** | −213.14 | −246.13*** | −287.70*** | −559.52** |
| | (−4.65) | (−3.08) | (−1.26) | (−5.82) | (−2.73) | (−2.30) |

- direct effects of being targeted by a trade action range between −14 and −42 bps

→ non-spatial OLS model overestimates direct effect (−83 bps)

- feedback loops from industry $i$ back to industry $i$ via other industries account for 7% to 20% of direct effects

→ **input-output relations amplify the responses of targeted industries**

- spillover effects range between −152 and −560 bps and are 5 to 18 times the size of direct effects

⇒ **global supply chains raise the costs of interventionist trade policy**

#### Spatial Panel Models II

| Panel A: Estimates | $CR_t$ (1) | (2) | (3) |
|---|---|---|---|
| $target_t$ | −33.88* | −35.98*** | −39.35*** |
| | (−1.78) | (−3.14) | (−2.84) |
| $US_t$ | −21.68 | 1.50 | −12.77 |
| | (−0.73) | (0.20) | (−0.59) |
| $W \times target_t$ | −152.71*** | | 9.64 |
| | (−4.64) | | (0.40) |
| $W \times US_t$ | 20.37 | | 16.31 |
| | (0.65) | | (0.72) |
| $W \times CR_t$ | | 0.88*** | 0.88*** |
| | | (98.07) | (88.58) |
| Event FE | Yes | Yes | Yes |
| Industry FE | No | No | No |
| Observations | 8512 | 8512 | 8512 |
| $R^2$ | 0.199 | 0.576 | 0.577 |
| **Panel B: Marginal Effects** | | | |
| Direct Effects | | | |
| $target_t$ | −33.88* | −39.24*** | −42.05*** |
| | (−1.78) | (−3.11) | (−3.03) |
| $US_t$ | −21.68 | 1.49 | −11.88 |
| | (−0.73) | (0.18) | (−0.55) |
| Spillover Effects | | | |
| $target_t$ | −152.71*** | −268.75*** | −208.42 |
| | (−4.64) | (−3.03) | (−1.22) |
| $US_t$ | 20.37 | 10.14 | 43.41 |
| | (0.65) | (0.18) | (0.61) |

- explicitly distinguishing between targeted and U.S. industries does not change previous conclusions
- import protection for domestic industries does neither benefit those industries directly nor any other industry through "virtuous" propagation

⇒ **protectionism does not benefit domestic industries**