The Effect of the U.S.-China Trade War on U.S. Investment [1]

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[1] The views expressed in this paper are those of the authors and do not necessarily represent those of the Federal Reserve Bank of New York or the Federal Reserve System.

How did the trade war affect aggregate investment?

- A problem with differences-in-differences estimators is that they identify *relative* effects not *total* effects
- We develop a new methodology to estimate the effect of an event on the stock prices of treated *and* untreated firms
  - We use the fact that unanticipated trade-war announcements move *both* aggregate and differential stock returns to identify the effect of the announcements on all firms
  - We embed these estimates into a q-theory investment model that maps firm market value into investment rates
- We *exactly* decompose an event's impact on stock-price movements into the
  - Common Effect: Effect of announcement on all firms through variables that matter "in general"
  - Differential Effect: Relative effect of the announcement on treated firms in the event window

Theoretical contribution

- Integrate event studies into factor models
  - An event moves aggregate returns by affecting all firms through the event's impact on common factors and also differentially affecting the returns of treated firms
- Show how to map the impact of an event on stock prices into investment
  - An event affects stock returns
  - Changes in stock prices imply changes in the returns to capital as measured by market-to-book (MTB) values (i.e., Tobin's q)
  - Changes in returns to capital change investment rates
- The stock-price investment link is closely related to two parameters governing
  - How stock-price movements change MTB values
  - How MTB values change investment rates

Results

- We find U.S. and Chinese tariff announcements in 2018-19 lowered U.S. aggregate equity prices by 6.0 percent
  - 3.4 percentage points is due to "Common Effect" - the impact of an announcement during an event window arising from two possible channels
    - How an event moves common factors during an event window
    - The average abnormal return of all firms during an event window
  - 2.6 percentage points is due to the "Differential Effect" - movement of treated firms relative to untreated firms during an event window
    - We define treated firms to be those that import from China, export to China, or have sales in China through affiliates
- We estimate that U.S.-China tariff announcements will lower U.S. investment by 1.9 percent by the fourth quarter of 2020
  - Over half of this drop is due to the common effect, which would be missed in a typical differences-in-differences estimation

Related literature

- Trade Event Studies
  - Grossman and Levinsohn (1989); Fisman et al (2014), Huang et al (2019), Greenland et al (2019), Bianconi et al (2019) examine how trade variables differentially affect the returns of firms
- Role of Trade Policy Uncertainty
  - Handley and Limao (2015), Pierce and Schott (2016), and Caldara et al (2019) examine impacts of uncertainty on firm behavior
- Use of Micro Data to Identify General Equilibrium Parameters
  - Nakamura and Steinsson (2018) examine monetary non-neutrality in high frequency data and Wolf (2019) examines consumer demand
- Literature on granularity
  - Gabaix (2011) and Gabaix and Koijen (2019) show how to decompose aggregate movements into common factors and granular residuals
- Factor Model Estimation
  - Bai and Ng (2002); Bai and Ng (2013) show how to estimate factor models and identify the number of common factors that move stock prices
- Estimation of q-Theory Models
  - Hayashi (1982), Frank and Shen (2016), Peters and Taylor (2017), Erickson and Whited (2012), Erickson et al (2014), Abel and Panageas (2020)

Theory

Factor Models

- We assume that the expected return of a stock can be written as a function of K *common factors* (which are chosen by a selection criterion)

$$r_{ft} = \alpha_f + \sum_{k=1}^{K} \beta_{kf} \delta_{kt} + \epsilon_{ft}$$

- A factor (δ_{kt}) is common if $\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \left(\delta_{kt} - \overline{\delta_k}\right)^2 > 0$
- r_{ft} is the percentage change in share price for firm f on day t
- α_f is the long-run rate of return for the firm
- β_{kf} (the factor loading) captures how the stock moves with factor δ_{kt}
- ϵ_{ft} is an error term

Identification

Stock-Market Event Studies

- Define D_{jt}^{w} to be an indicator variable that is one if day t falls w days after event j and zero otherwise
- An event study consists of an estimation of the form

$$\epsilon_{ft} = \theta_t + \sum_{j \in \Omega^{UC}} \sum_{i=1}^{N} \gamma_{ij} Z_{if} D_{jt}^{w} + \nu_{ft} \quad \forall j, t \text{ s.t. } D_{jt}^{w} > 0,$$

- where Ω^{UC} is the set of (U.S.- and Chinese-tariff) events and
  - θ_t is the average abnormal return on day t
  - γ_{ij} is a parameter
  - Z_{if} is a treatment variable, and $Z_{if} = 0$ for some untreated firm f
  - ν_{ft} captures idiosyncratic shocks to firm share prices

- We can think of D_{jt}^{w} as a factor, but because $\lim\limits_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \left(D_{jt}^{w} - \overline{D_{j}^{w}} \right)^2 = 0$, it is not a *common factor* (i.e., it does not matter in general)

The Daily Decomposition of Firm Stock Price Movements

- After estimating the factor model and event study, we can decompose the firm's rate of return on a day as

$$r_{ft} = \hat{\alpha}_f + r_{ft}^C + r_{ft}^D + \hat{\nu}_{ft},$$

where

$$r_{ft}^C \equiv \sum_{k=1}^{K} \hat{\beta}_{kf} \hat{\delta}_{kt} + \hat{\theta}_t \quad \text{and} \quad r_{ft}^D \equiv \sum_{j \in \Omega^{UC}} \sum_{i=1}^{N} \hat{\gamma}_{ij} Z_{if} D_{jt}^w.$$

- r_{ft}^C captures how information released on day t affects the return of a firm through two channels:
  - Common factors: $\sum_{k=1}^{K} \hat{\beta}_{kf} \hat{\delta}_{kt}$
  - An event-specific factor that has a common impact on firms: $\hat{\theta}_t$
- r_{ft}^D captures the differential effect

Decomposing Daily Aggregate Stock-Price Movements

- The rate of return of a stock price index (R_t) is a weighted average of the return of each individual stock: $R_t = \sum_f S_{f,t-1} r_{ft}$, where $S_{f,t-1}$ are the weights applied to individual stock returns and $\sum_f S_{f,t-1} = 1$.

- This enables us to write the exact decomposition of the stock market index return on a day as

$$R_t = \underbrace{\sum_f S_{f,t-1}\hat{\alpha}_f}_{R_t^\alpha} + \underbrace{\sum_f S_{f,t-1} r_{ft}^C}_{R_t^C} + \underbrace{\sum_f S_{f,t-1} r_{ft}^D}_{R_t^D} + \underbrace{\sum_f S_{f,t-1}\hat{\nu}_{ft}}_{R_t^I},$$

- R_t^C captures how the common effect moved the market
- R_t^D captures how the differential returns of firms exposed to China moved aggregate returns on day t
- We can also aggregate to quarterly frequency (s), which will render the data compatible with quarterly investment data Quarterly Frequency

From Stock Prices to Investment

- The q-theory of investment gives the following relationship between investment and a firm's market-to-book (MTB) value: Derivation

$$\frac{I_{fs}}{K_{fs}} = \rho_f - \frac{p_s}{\psi} + \psi^{-1}\frac{V_{fs}}{K_{fs}} - \chi_{fs}$$

where

- I_{fs} is firm f's investment during quarter s
- K_{fs} is the initial capital stock
- ρ_f is the depreciation rate
- p_s is the price of investment goods
- $0 < \psi < \infty$ is a parameter that reflects the cost of adjusting the firm's capital stock
- V_{fs} is the initial market value of the firm's assets
- χ_{fs} is a term related to measurement error

Trade and Investment

- Totally differentiating the investment equation yields

$$dI_{fs} = \frac{I_{fs}}{K_{fs}} dK_{fs} - \frac{dp_s}{\psi} K_{fs} + \psi^{-1} K_{fs} d\frac{V_{fs}}{K_{fs}} - K_{fs} d\chi_{fs}$$

- We can write the movement in MTB due to share price changes as

$$d\frac{V_{fs}}{K_{fs}} = \lambda_C \bar{r}_{fs}^C + \lambda_D \bar{r}_{fs}^D + \lambda_\nu \bar{\nu}_{fs} + \lambda_r \left(\bar{r}_{fs} - \bar{r}_{fs}^C - \bar{r}_{fs}^D - \bar{\nu}_{fs}\right)$$

- where the λ's are parameters that link movements in stock prices to movements in MTB
- We can write the impact of an event on investment as

$$dI_{fs}^E \equiv \psi^{-1} K_{fs} \left(\lambda_G \bar{r}_{fs}^C + \lambda_D \bar{r}_{fs}^D\right)$$

- Summing this expression across all firms and dividing both sides by aggregate investment (I_s) produces

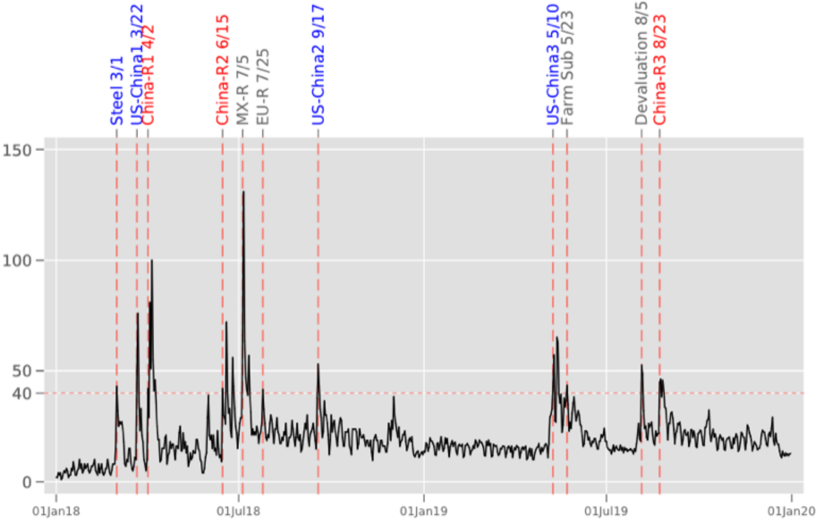
$$\frac{dI_s^E}{I_s} \equiv \frac{\psi^{-1}\lambda_C \sum_f \bar{r}_{fs}^C K_{fs}}{I_s} + \frac{\psi^{-1}\lambda_D \sum_f \bar{r}_{fs}^D K_{fs}}{I_s}$$

Discrete Version

Data

Google "Trade War" Searches (Ngrams)

Methodology Individual Events



- US and Chinese tariff events are marked in blue and red, respectively.
- Market fell in total 8.9% on US-China event days and 2.9% over a 7-day window

Firm Selection

- Our sample of firms consists of all listed firms for which we have CRSP data for 2016 to 2019
- Identifying the production network
  - We merge these data with data from Capital IQ using DUNS numbers to identify all the subsidiaries of each firm
    - For example, Beats Electronics is part of the Apple Network
  - We merge these data with FactSet to identify the principal suppliers to the firm or any of its subsidiaries
    - Foxconn (Hon Hai) would be counted as part of the Apple Network
  - Share of firm revenues (exports plus affiliate sales) from China from FactSet
  - We use Datamyne data from 2017 to identify firms exporting to and importing from China by sea Details

Importance of Supply Chains in Understanding Trade

China Export and Import Dummies

	Mean
Firm Imports from China	0.07
Firm or Subsidiary Imports from China	0.23
Firm, Subsidiary, or Supplier Imports from China	0.27
Firm Exports to China	0.01
Firm or Subsidiary Exports to China	0.04
Firm Exposed to China	0.46
Number of Firms: 2,864	

Large Firms are More Exposed

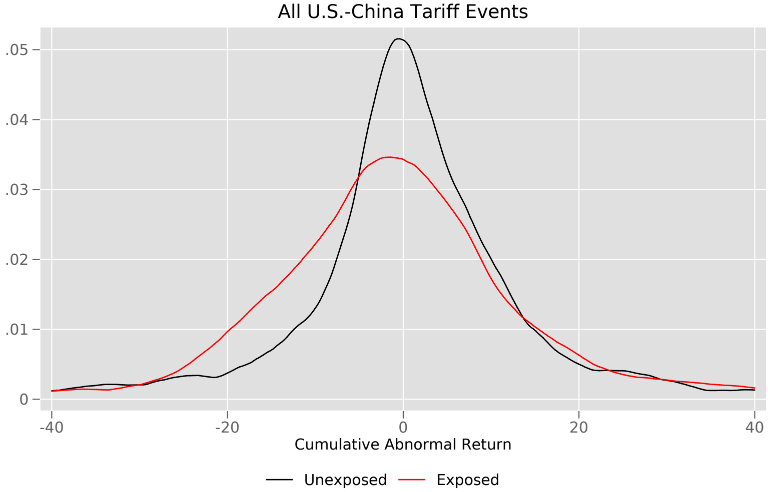
Large Firms Import from, Export to, and Sell More in China

	All Firms	Top 25	Top 50	Top 100
Cumulative Share of Market Capitalization	1	0.31	0.43	0.56
Average China Import Dummy	0.27	0.72	0.60	0.60
Average China Export Dummy	0.043	0.20	0.18	0.16
Average China Revenue Share	0.023	0.066	0.086	0.061
Average Non-China Revenue Share	0.16	0.34	0.38	0.34

Estimation

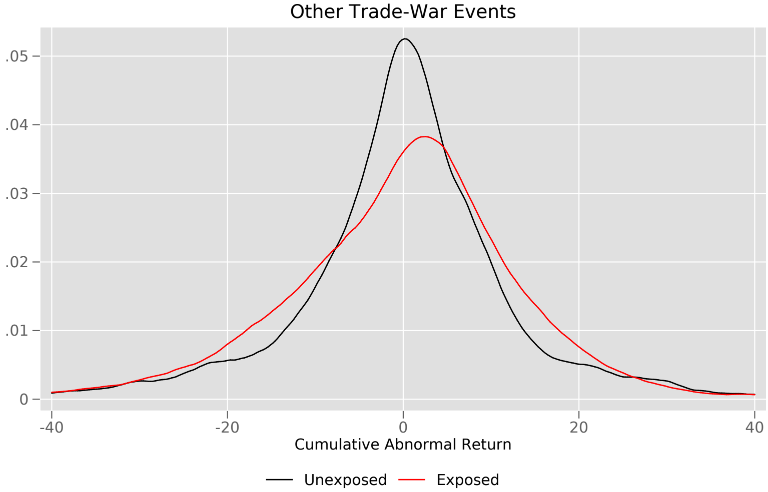
Dispersion in Returns: All US-China Events

Factor Model Results | US Events | Chinese Events



Placebo: Other Trade-War Events

Individual Event Days



US Tariff Events (7-Day Windows)

Dep. Var.: $\hat{\epsilon}_{ft}$	Average	01Mar18 Steel and Aluminum Announcement	22Mar18 China Target Announcement	17Sep18 \$200 Billion Announcement	10May19 10-25% Tariff Increase Announcement
China Importer	-0.074***	-0.252***	0.083**	-0.025	-0.102**
	(0.021)	(0.044)	(0.038)	(0.042)	(0.047)
China Exporter	-0.023	-0.116*	-0.045	0.095	-0.027
	(0.035)	(0.067)	(0.064)	(0.085)	(0.062)
China Revenue Share	-0.619***	0.253	-0.903***	0.775***	-2.601***
	(0.146)	(0.264)	(0.279)	(0.240)	(0.370)
Decomposition of Market Return in Percent					
Market Return	-3.50	0.28	-3.39	0.32	-0.70
Differential Effect	-2.13	-0.99	-0.04	0.26	-1.36
Common Effect	-2.69	2.15	-2.62	-0.60	-1.62
Total Event Effect	-4.82	1.16	-2.66	-0.34	-2.98

3 Day

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Total Event Effect	-4.82	1.16	-2.66	-0.34	-2.98

3 Day

Chinese Tariff Events (7-Day Windows)

Dep. Var.: $\hat{\epsilon}_{ft}$	Average	02Apr18 China $128 Bln Announcement	15Jun18 China $50 Bln Announcement	23Aug19 China Soy/Auto Announcement
China Importer	0.046*	0.027	-0.046	0.158***
	(0.025)	(0.039)	(0.044)	(0.044)
China Exporter	-0.056	0.059	-0.183***	-0.045
	(0.037)	(0.057)	(0.063)	(0.069)
China Revenue Share	-0.825***	-0.417	-1.699***	-0.360
	(0.144)	(0.270)	(0.244)	(0.230)
Decomposition of Market Return in Percent				
Market Return	-0.80	-0.29	-0.53	0.03
Differential Effect	-0.48	0.01	-0.95	0.46
Common Effect	-0.67	-0.44	0.73	-0.95
Total Event Effect	-1.15	-0.43	-0.23	-0.50

3 Day

Robustness Tests

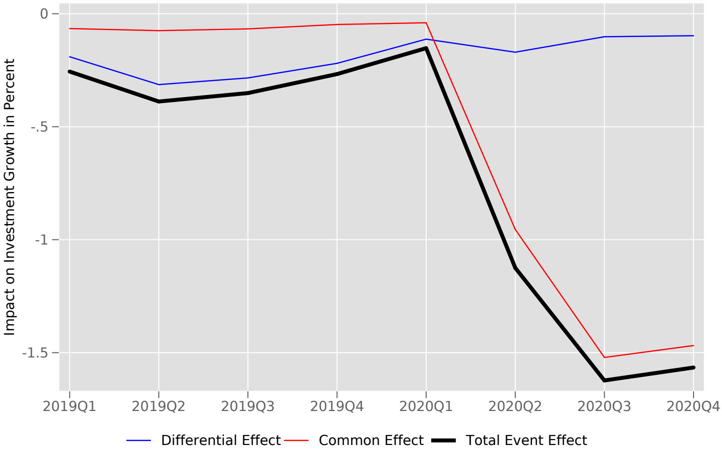
- Robustness to Alternative Window Lengths
  - 3-Day Windows 3-Day
  - Decompositions by Window Lengths 3-30 Day Windows
- Placebo Tests: Other Events and Large Stock-Market Declines Placebo 3-Day
- Dropping Revenue Share Revenue Share 3-Day
- Omitted Variables and Factors: Industry Protection, Size, Non-China Revenue Omitted 3 Day

Effects of Announcements on MTB and Investment

Robustness

Dep. Var.	$\frac{I_{f,s}}{K_{f,s-4}}$ OLS (1)	$\frac{I_{f,s}}{K_{f,s-4}}$ OLS (2)	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ OLS (3)	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ IV (4)	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ IV (5)	$\frac{I_{f,s}}{K^T_{f,s-4}}$ Cumulant (6)
$\text{MTB}_{f,s-4}$	0.013***	0.012***				0.015***
	(0.001)	(0.001)				(0.003)
$\text{Cashflow}_{fs}/K_{f,s-4}$		0.004***				0.229***
		(0.000)				(0.041)
$\Delta^4\text{MTB}_{f,s-4}$			0.012***	0.009***	0.008***	
			(0.001)	(0.002)	(0.002)	
$\Delta^4\left(\text{Cashflow}_{fs}/K_{f,s-4}\right)$			0.008***	0.008***	0.008***	
			(0.001)	(0.001)	(0.001)	
N	30,780	29,698	16,522	14,390	14,390	21,615
Overid J-testχ^2				5.87		3.51
[p value]				[0.12]		[0.06]
Weak IV F-test				1,635.0	6,504.7	
First Stage				$\Delta^4\text{MTB}_{f,s-4}$	$\Delta^4\text{MTB}_{f,s-4}$	
$\tilde{r}^C_{f,s-4}$				1.255**		
				(0.542)		
$\tilde{r}^D_{f,s-4}$				3.207***		
				(0.470)		
$\tilde{\nu}_{f,s-4}$				1.001***		
				(0.063)		
$\dot{r}_{f,s-4}$				0.969***		
				(0.012)		
$\tilde{r}_{f,s-4}$					0.973***	
					(0.012)	
First stage F-test				1,635	6,505	
[p value]				[0.00]	[0.00]	

Investment Impact



Underlying Data

Conclusion

- We develop a new method of quantifying the impact of policy announcements on investment rates that makes use of stock market data
  - We use the fact that an event moves both aggregate and differential stock returns to identify the impact of the announcement through common factors and through the treatment effect
- We estimate the investment impact of events by embedding the implied changes in the returns to capital into a structural q theory of investment model
- We estimate that U.S. and Chinese tariff announcements lowered equity prices by 6.0 percentage points
  - A $1.7 trillion decline in market value
- This will lower U.S. investment by 1.9 percentage points between 2018Q4 and 2020Q4

Thank You

Multi-Factor Extension

- Let the return of all stocks in the market be given by

$$\mathbf{R_t} = \mathbf{M} + \mathbf{B}\mathbf{D_t} + \mathbf{e_t}, \quad t = 1, ..., T \tag{1}$$

  where $\mathbf{R_t} = [r_{1t} \cdots r_{Ft}]'$ is an $F \times 1$ vector of percentage stock price changes for each firm on each day

- $\mathbf{M} = [\mu_1 \cdots \mu_F]'$ is an $F \times 1$ vector of constants
- $\mathbf{B} = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1q} \\ \vdots & & \vdots \\ \beta_{F1} & \cdots & \beta_{Fq} \end{bmatrix}$ is the $N \times q$ matrix of factor loadings,
- $\mathbf{D_t} = [\delta_{1t} \cdots \delta_{qt}]'$ is the $q \times 1$ vectors of (unobserved) factors,
- $\mathbf{e_t} = [e_{1t} \cdots e_{Ft}]'$ is the $F \times 1$ vectors of errors.
- Let $\mathbf{X_t} = \mathbf{D_t} - \mathbf{M}$, and we can equivalently write

$$\mathbf{X_t} = \mathbf{B}\mathbf{D_t} + \mathbf{e_t}, \quad t = 1, ..., T \tag{2}$$

Back

Orthogonality Assumptions

- While there are different factor models, two assumptions that are common to all factor models are
  A1. Both factors and residuals are mean zero variables: $E(\mathbf{D_t}) = 0$ and $E(\mathbf{e_t}) = 0$
  A2. Errors are uncorrelated with factors: $E(\mathbf{D_t}\mathbf{e_t}^{'}) = 0$
    - These two assumptions imply $\mathbf{\Sigma} = \mathbf{B\Omega B} + \mathbf{\Sigma_e}$
    - where
      - $\mathbf{\Omega} = E(\mathbf{D_t}\mathbf{D_t}^{'})$ denotes the covariance matrix of factors,
      - $\mathbf{\Sigma} = E(\mathbf{X_t}\mathbf{X_t}^{'})$ denotes the covariance matrix of the observed variable,
      - $\mathbf{\Sigma_e} = E(\mathbf{e_t}\mathbf{e_t}^{'})$ denotes the covariance matrix of the errors
- Errors may be cross-sectionally and serially correlated Back

Factor Indeterminacy

- Without further assumptions, $\mathbf{B}$ and $\mathbf{D_t}$ are not separately identifiable from

$$\mathbf{X_t} = \mathbf{B}\mathbf{D_t} + \mathbf{e_t}$$

  - To see this, note that for an arbitrary $q \times q$ invertible matrix $\mathbf{A}$, we can define

$$\mathbf{X_t} = (\mathbf{B}\mathbf{A}^{-1})(\mathbf{A}\mathbf{D_t}) + \mathbf{e_t},$$

    which is observationally equivalent to the factor model

- In order to uniquely fix $\mathbf{D}$ and $\mathbf{B}$, we require q^2 additional normalizations Back

Estimation (Bai and Ng 2013)

- The principal components estimators for (Λ, F) are obtained by minimizing

$$\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{ft} - \mathbf{B_f}'\mathbf{D_t})^2 = \text{tr}[(\mathbf{X} - \mathbf{DB}')(\mathbf{X} - \mathbf{DB}')'] \tag{3}$$

where we make the following normalizations:

- $\frac{1}{T}\sum_{t=1}^{T}\mathbf{D_t}\mathbf{D_t}' = \mathbf{I_q}$, which provides $q(q+1)/2$ restrictions
- We require $\mathbf{B}'\mathbf{B}$ to be diagonal, which provides another $q(q-1)/2$ restrictions Back

How Many Factors Are There?

- Let k be the potential number of factors and $(\widehat{\mathbf{B}}_{\mathbf{i}}^{\mathbf{k}}, \widehat{\mathbf{D}}_{\mathbf{t}}^{\mathbf{k}})$ be the principal components estimators obtained by assuming $q = k$ factors.
  - The sum of squared residuals can be viewed as a function of k:

$$V(k) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{ft} - \widehat{\mathbf{B}}_{\mathbf{i}}^{\mathbf{k}\prime} \widehat{\mathbf{D}}_{\mathbf{t}}^{\mathbf{k}})^2 \tag{4}$$

  - Bai and Ng (2002) recommend the following loss function when errors may be cross-sectionally correlated:

$$IC(k) = \ln(V(k)) + k\left([N + T - k] \frac{\ln(NT)}{NT} \right),$$

  - and propose choosing the number of factors to minimize this loss function

$$\hat{k}_{IC} = \arg \min_{0 \leq k \leq k^{max}} IC(k), \tag{5}$$

  where k^{max} is the upper bound of the true number of factors q Back

Changing the Frequency

- We defined the decomposition of returns at a *daily* frequency but we can also do the decomposition for any event j for each component X:

$$R_j(w) \equiv \sum_{\ell=-1}^{w} R_{j+\ell} \text{ and } R_j^X(w) \equiv \sum_{\ell=-1}^{w} R_{j+\ell}^X \text{ for } X \in \{C, D, I\}$$

- Since investment is reported at a quarterly frequency, it will also be useful to do our firm-level decomposition at the same frequency, so we define

$$\bar{X}_{fs} \equiv \sum_{t=F(s)}^{L(s)} X_{ft}, \text{ for } X \in \left\{r_{ft}, r_{ft}^C, r_{ft}^D, \hat{\nu}_{ft}, \hat{\epsilon}_{ft}\right\},$$

where $F(s)$ is the first trading day in quarter s; $L(s)$ is the last trading day

- Finally, it will also be useful to sometimes aggregate over four quarters:

$$\tilde{X}_{fs} \equiv \sum_{\ell=s-3}^{s} \bar{X}_{f\ell} \quad \text{for} \quad X \in \left\{r, r^C, r^D, \nu\right\}$$

Back

A q Theory of Investment

- At the start of any period s, managers produce based on the firm's existing capital stock, K_{fs}. This production yields a flow of revenues equal to $A_{fs}g\left(K_{fs}, L_{fs}\right)$, where A_{fs} captures the firm's productivity (and output price), and L_s is labor

- Firms then choose an amount to be invested, I_{fs}, and pay the remainder to shareholders in the form of dividends

$$\pi_{fs} = A_{fs}g\left(K_{fs}, L_{fs}\right) - w_s L_{fs} - p_s I_{fs} - \frac{\psi}{2}\left(\frac{I_{fs}}{K_{fs}} - \rho_f\right)^2 K_{fs},$$

- where w_s is the wage; p_s is the cost of the investment good; I_{fs} is the amount of investment; ρ_f is the depreciation rate; and $0 \leq \psi < \infty$ tells us how costly it is for firms to adjust their capital stock from the one in the previous period
    - The last term is the adjustment cost that arises if a firm tries to change its capital stock Back

The Firm Problem

- Firms maximize the PDV of dividends
$$V_{fs} = \sum_{\ell=s}^{\infty} \left(\frac{1}{1+r} \right)^{\ell-s} \pi_{f\ell} = \pi_{fs} + \frac{V_{fs+1}}{1+r}$$
- This can be rewritten as maximizing the following Lagrangian equation:

$$\begin{aligned} L_s = \sum_{\ell=s}^{\infty} \left(\frac{1}{1+r} \right)^{\ell-s} & \{ A_{fs} g\left(K_{fs}, L_{fs}\right) - w_s L_{fs} \\ & - p_s I_{fs} - \frac{\psi}{2} \left(\frac{I_{fs}}{K_{fs}} - \rho_f \right)^2 K_{fs} - q_{fs} \left[K_{f,s+1} - \left(1 - \rho_f\right) K_{fs} - I_{fs} \right] \} \end{aligned}$$

- The first-order condition with respect to investment is given by
$$q_{fs} = p_s + \psi \left(\frac{I_{fs}}{K_{fs}} - \rho_f \right)$$

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The Investment Equation

- Rearranging terms gives us

$$\frac{I_{fs}}{K_{fs}} = \rho_f - \psi^{-1} p_s + \psi^{-1} q_{fs}$$

- Written this way, it makes clear that a reduction in the shadow value of capital (q_{fs}) reduces the investment rate

- Hayashi (1982) showed that if the production function exhibits constant returns and adjustment costs are homogeneous of degree one in investment and capital, we can rewrite this in terms of a firm's (lagged) "market-to-book" value:

$$\frac{I_{fs}}{K_{fs}} = \rho_f - \frac{p_s}{\psi} + \psi^{-1} \frac{V_{fs}}{K_{fs}} + \chi_{fs}$$

where χ_{fs} is a term related to measurement error Back

Discrete Version

- Usually IK regressions assume that last period is last year, so for us this implies

$$\frac{I_{fs}}{K_{f,s-4}} = \rho_f - \frac{p_s}{\psi} + \psi^{-1}\frac{V_{f,s-4}}{K_{f,s-4}} - \chi_{fs}$$

- MTB may be mismeasured, so we may want to instrument. The components of stock movements may be good instruments for changes in MTB. 4-quarter differencing the investment equation yields

$$\Delta^4\left(\frac{I_{fs}}{K_{fs}}\right) = \Delta^4\frac{p_s}{\psi} + \psi^{-1}\Delta^4\left(\frac{V_{f,s-4}}{K_{f,s-4}}\right) - \Delta^4\chi_{fs}$$

- Defining $\dot{r}_{fs} \equiv \tilde{r}_{fs} - \tilde{r}^C_{fs} - \tilde{r}^D_{fs} - \tilde{\nu}_{fs}$, we have

$$\Delta^4\left(\frac{V_{fs}}{K_{fs}}\right) = \eta_f + \eta_t + \lambda_C\tilde{r}^C_{fs} + \lambda_D\tilde{r}^D_{fs} + \lambda_\nu\tilde{\nu}_{fs} + \lambda_r\dot{r}_{fs} + \zeta_{fs}$$

- So the impact of the common and differential effects on investment can be written as

$$\frac{\Delta^4 I^P_s}{I_{s-4}} \equiv \frac{\widehat{\psi^{-1}}\hat{\lambda}_C\sum_f \tilde{r}^C_{f,s-4}K_{f,s-4}}{I_{s-4}} + \frac{\widehat{\psi^{-1}}\hat{\lambda}_D\sum_f \tilde{r}^D_{f,s-4}K_{f,s-4}}{I_{s-4}}$$

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Identifying Event Dates

- Some studies use March 22, 2018 as the main event date
    - Problem there were earlier and later announcements, so might have different results if chose different days
- We use "Google Trends" to identify dates in 2018 and 2019 and count the number of searches for "trade war" (G_t) on day t
- A trade event begins on day t if $G_t \geq \overline{G}$ and for $s \in \{1, 2, ..., 5\}$, $\overline{G} > G_{t-s}$ where $\overline{G}$ is some threshold
    - In this case we set our trade event indicator $I_t = 1$; $I_t = 0$ otherwise.
    - We chose $\overline{G}$ sufficiently high to catch the major days with a spike in trade war searches
    - We identify the event as either the day of the spike or the day before the spike (if the main trade war story broke the day before)
- Divide events into "US tariff", "China retaliation", and "Placebo" events Back

Stock Returns on Event Dates

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Event Group	Event Date	R_t (%)	$\sum_{t-1}^{t+5} R_t$ (%)	Description
US	01Mar18	-1.16	0.28	US announces steel and aluminum tariffs
US	22Mar18	-2.48	-2.70	US orders identification of Chinese products for tariffs
CHN	02Apr18	-2.25	0.39	China to impose tariffs on 128 US exports
CHN	15Jun18	-0.10	-0.53	China retaliates on $50 bn of US imports
OTH	05Jul18	0.88	2.61	Mexico imposes retaliatory tariffs on dozens of US goods
OTH	25Jul18	0.84	-0.08	EU prepares retaliatory tariffs on $20 bn in US goods
US	17Sep18	-0.67	0.32	US announces tariffs on $200 bn goods from China
US	10May19	0.39	-0.70	US raises tariffs from 10 to 25 percent on $200 bn of Chinese imports
OTH	23May19	-1.29	-4.08	US announces $16 bn bailout to farmers hurt by trade war
OTH	05Aug19	-3.00	-2.48	Chinese currency fell to the lowest point since 2008
CHN	23Aug19	-2.60	0.03	China raises tariffs on soy and autos
US+CHN	all	-8.87	-2.93	

Identifying China Importers, Exporters and MNCs

- Datamyne has information on all seaborne trade by firm country, and HS6 category
  - but the HS6 is not really usable because lots of firms have goods that are linked to a very aggregated HS2 category, so we only used the firm-country dimension
- We merge these data with Datamyne data for 2017 using firm names
- Note one limitation of Datamyne data is that it only covers seaborne trade
  - 46 percent of imports overall
  - But seaborne trade accounts for 62 percent of the value of US imports from China and 58 percent of US exports to China Other Countries
- We say a firm imports from (exports to) a country if the firm, its subsidiaries, or principle suppliers appear as importers from that country in the Datamyne data Major Exporters Major Importers
- We also use data from FactSet to measure the share of revenue from China

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Much Of China-US Trade is by Sea

Percent of Seaborne Imports and Exports (2017)

Country	Import Share by Sea	Export Share by Sea
Canada	0.05	0.03
China	0.62	0.58
Germany	0.57	0.36
Japan	0.73	0.50
South Korea	0.69	0.51
Mexico	0.08	0.12
United Kingdom	0.47	0.31
World Total	0.46	0.34

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Top Exporters to China

Top Exporters with China

Rank	Company Name	Value of Exports to China	Percent of Total Market Cap
1	EXPEDITORS INTERNATIONAL WA INC	1716	0.31
2	TYSON FOODS INC	900	0.64
3	INTERNATIONAL PAPER CO	581	0.66
4	CATERPILLAR INC	350	2.49
5	DOMTAR CORP	345	0.08
6	3M CO	312	3.74
7	RAYONIER INC NEW	272	0.11
8	CH ROBINSON WORLDWIDE INC	261	0.33
9	Y R C WORLDWIDE INC	245	0.01
10	LANDSTAR SYSTEM INC	170	0.12

Top Exporters with China - Direct

Rank	Company Name	Value of Direct Exports to China	Percent of Total Market Cap
1	EXPEDITORS INTERNATIONAL WA INC	1716	1.55
2	3M CO	312	18.93
3	RAYONIER INC NEW	272	0.56
4	CH ROBINSON WORLDWIDE INC	261	1.69
5	SCHNITZER STEEL INDUSTRIES INC	53	0.13
6	VALMONT INDUSTRIES INC	16	0.51
7	KIMBERLY CLARK CORP	11	5.65
8	WERNER ENTERPRISES INC	10	0.38
9	HANESBRANDS INC	8	1.05
10	HAIN CELESTIAL GROUP INC	6	0.59

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Top Importers from China

Top Importers with China

Rank	Company Name	Value of Imports to China	Percent of Total Market Cap
1	LOWES COMPANIES INC	2544	0.50
2	H P INC	1485	0.23
3	NEWELL RUBBERMAID INC	801	0.10
3	NEWELL BRANDS INC	801	0.10
5	DOLLAR GENERAL CORP NEW	581	0.17
6	CHEVRON CORP NEW	564	1.59
7	STANLEY BLACK & DECKER INC	552	0.17
8	VALERO ENERGY CORP NEW	502	0.27
9	GENERAL MOTORS CO	432	0.39
10	CATERPILLAR INC	422	0.61

Top Importers with China - Direct

Rank	Company Name	Value of Direct Imports to China	Percent of Total Market Cap
1	CATO CORP NEW	89	0.03
2	A C C O BRANDS CORP	86	0.11
3	IROBOT CORP	86	0.18
4	KIMBERLY CLARK CORP	66	3.40
5	HAVERTY FURNITURE COS INC	51	0.04
6	P V H CORP	47	0.87
7	D S W INC	46	0.13
7	DESIGNER BRANDS INC	46	0.13
9	GENESCO INC	42	0.06
10	PLUG POWER INC	37	0.04

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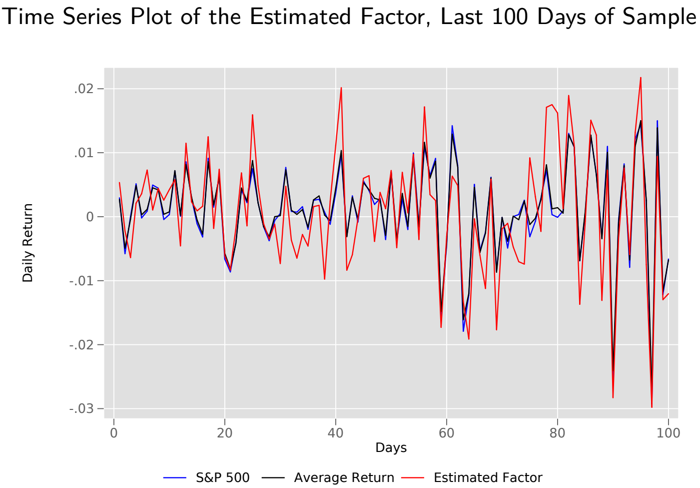
First Factor is Strongly Correlated with Avg Market Return



Correlation over full sample with Avg Return is 0.89 and with S&P 500 is 0.85 Back

One Factor Model is Similar to CAPM

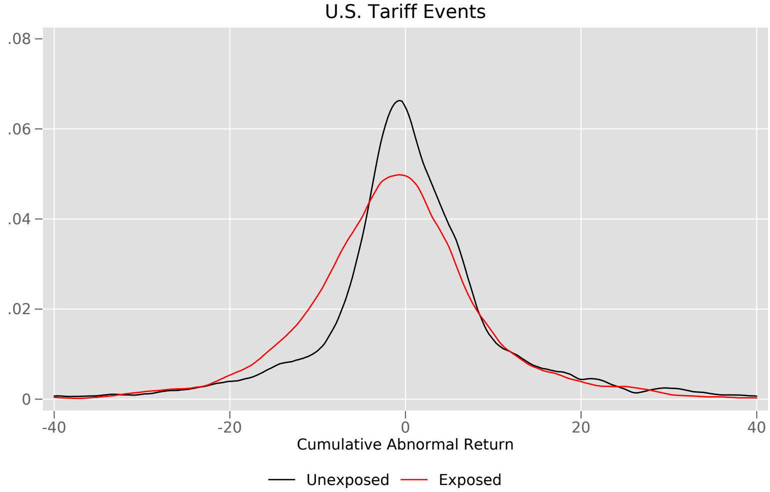
Estimated Factor 1 Loadings

	Count	Mean	sd	Min	p25	p50	p75	Max
α_f	2,864	0.001	0.001	-0.008	0.000	0.001	0.001	0.007
$\beta_{1,f}$	2,864	0.893	0.451	-0.481	0.602	0.881	1.143	4.068

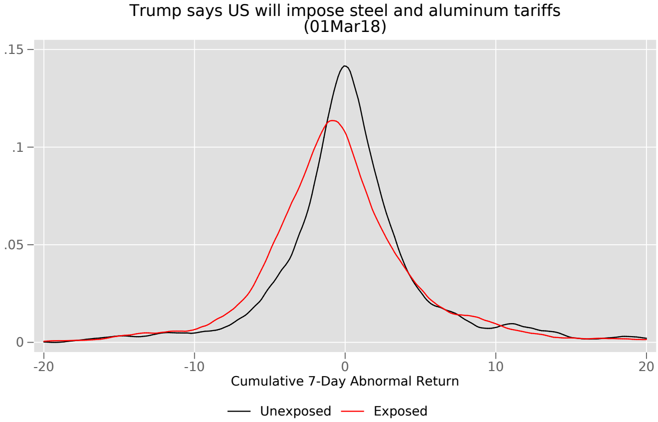
- Each factor adds 2,864 parameters
  - Factor 1 accounts for 10 percent of the variance
  - Factor 2 accounts for 2.0 percent of the variance
  - Factor 3 accounts for 1.6 percent of the variance
  - Factor 4 accounts for 1.5 percent of the variance
  - Factor 5 accounts for 1.5 percent of the variance
- The Bai and Ng (2002) procedure indicates that we should use 2 factors Back

Dispersion in Returns - US Tariff Events

Individual Event Days | Back



Dispersion in Returns - US Tariff Events



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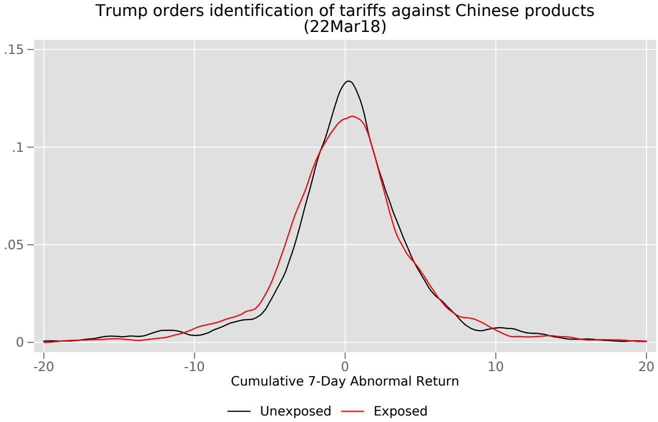
Dispersion in Returns - US Tariff Events



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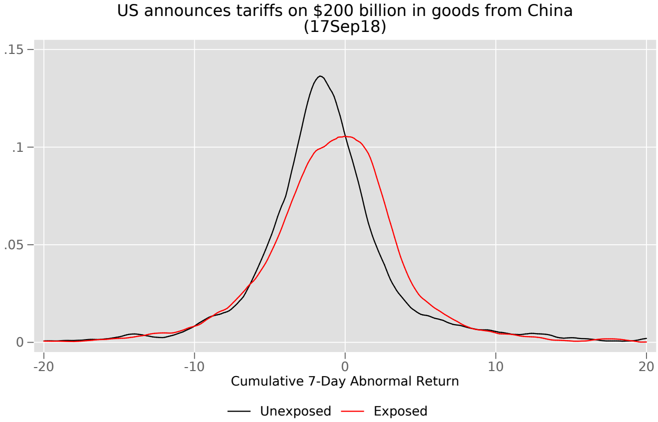
Dispersion in Returns - US Tariff Events



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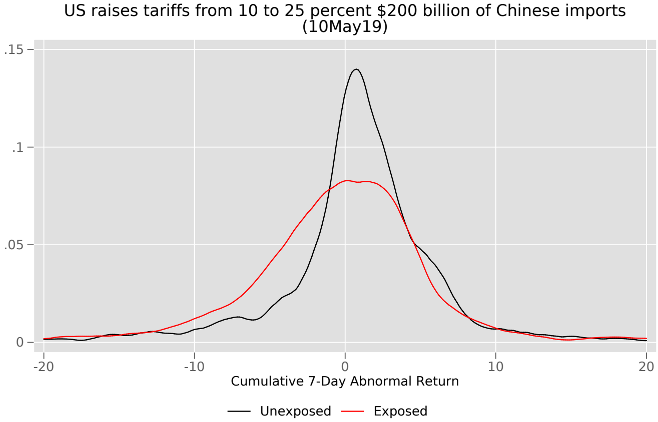
Dispersion in Returns - US Tariff Events



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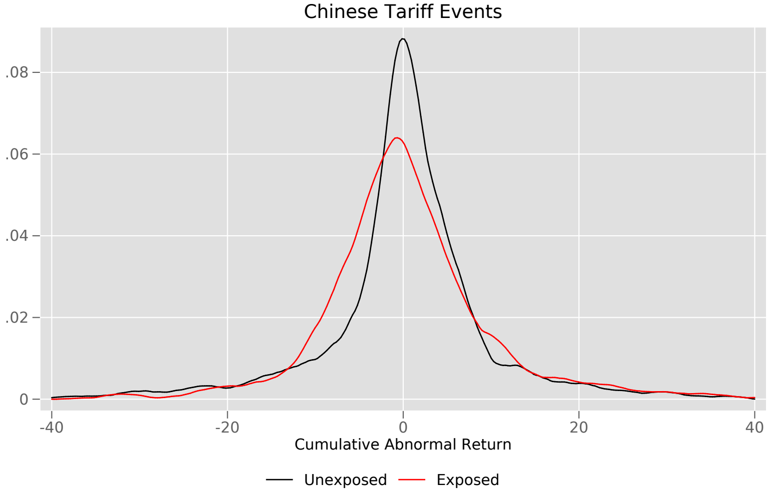
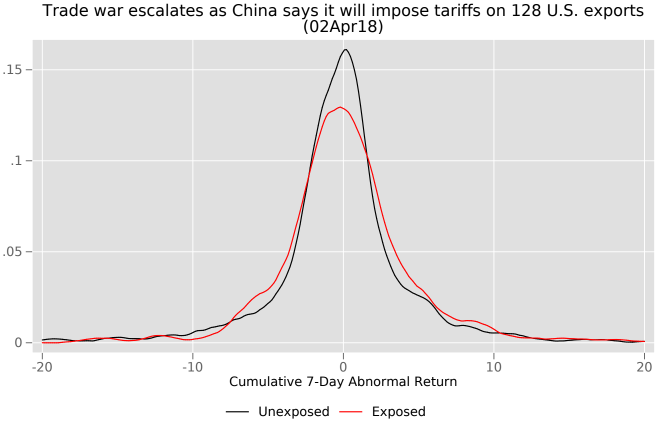
Dispersion in Returns - Chinese Retaliation

Individual Event Days   Back



Dispersion in Returns - Chinese Retaliation



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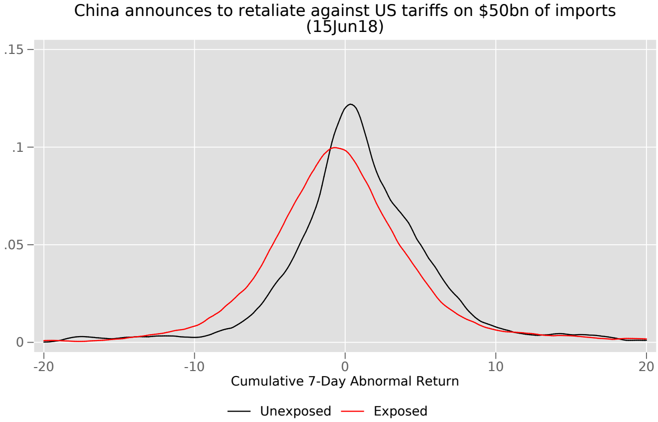
Dispersion in Returns - Chinese Retaliation



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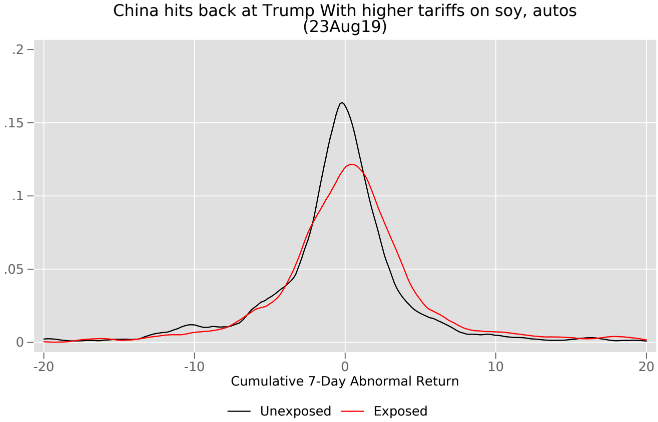
Dispersion in Returns - Chinese Retaliation



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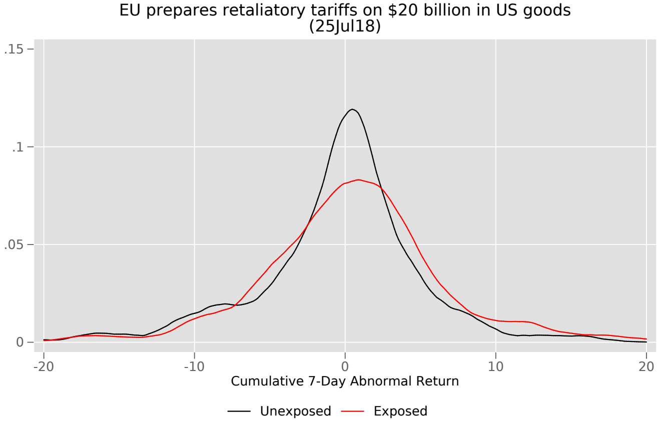
Dispersion in Returns - Placebo

Back

Dispersion in Returns - Placebo



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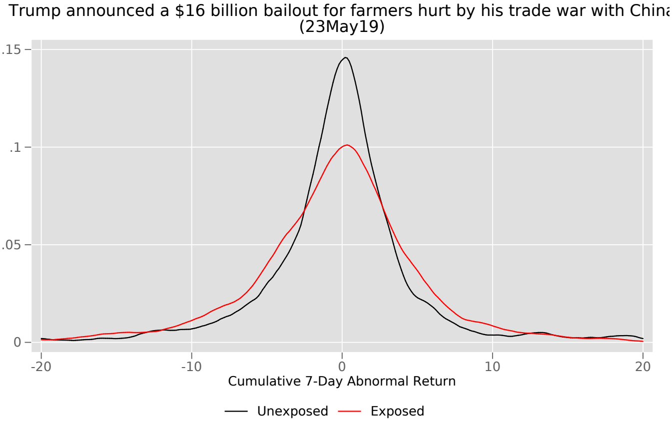
Dispersion in Returns - Placebo



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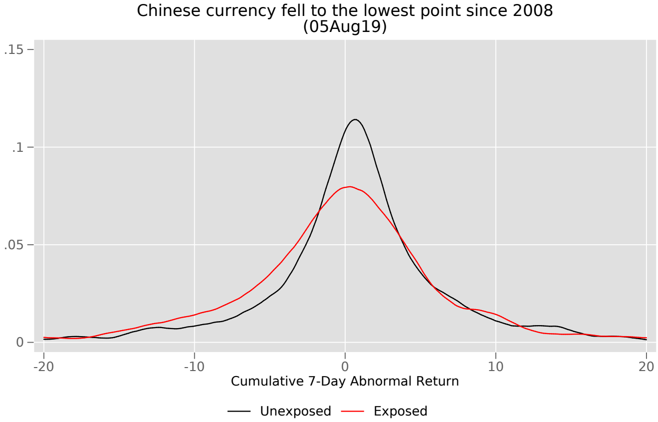
Dispersion in Returns - Placebo



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$t-1$ to $t+1$ CAR

Impact of US Tariffs on Importers, Exporters, and MNCs (7-Day Window)

Dep. Var.: $\hat{\epsilon}_{ft}$	Average	01Mar18 Steel and Aluminum Announcement	22Mar18 China Target Announcement	17Sep18 $200 Billion Announcement	10May19 10-25% Tariff Increase Announcement
China Importer	-0.076**	-0.275***	-0.114**	0.218***	-0.135*
	(0.034)	(0.073)	(0.058)	(0.058)	(0.079)
China Exporter	-0.080	-0.325***	-0.148*	0.224	-0.071
	(0.056)	(0.113)	(0.088)	(0.139)	(0.103)
China Revenue Share	-1.097***	-0.477	-1.223***	0.059	-2.746***
	(0.207)	(0.444)	(0.319)	(0.321)	(0.535)
Decomposition of Market Return in Percent					
Market Return	-8.63	-1.58	-4.66	-0.03	-2.37
Differential Effect	-1.31	-0.66	-0.43	0.46	-0.68
Common Effect	-5.58	0.04	-2.81	-0.55	-2.26
Total Event Effect	-6.89	-0.62	-3.24	-0.09	-2.94

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$t-1$ to $t+1$ CAR

Impact of Retaliation on Importers, Exporters, and MNCs (7-Day Window)

Dep. Var.: $\hat{\epsilon}_{ft}$	Average	02Apr18 China \$128 Bln Announcement	15Jun18 China \$50 Bln Announcement	23Aug19 China Soy/Auto Announcement
China Importer	0.008	0.066	-0.024	-0.018
	(0.038)	(0.064)	(0.065)	(0.067)
China Exporter	-0.074	0.183**	-0.205**	-0.200**
	(0.050)	(0.083)	(0.088)	(0.091)
China Revenue Share	-0.868***	0.112	-1.489***	-1.228***
	(0.246)	(0.539)	(0.361)	(0.355)
Decomposition of Market Return in Percent				
Market Return	-1.11	0.37	0.11	-1.59
Differential Effect	-0.44	0.20	-0.35	-0.29
Common Effect	-0.99	-0.21	0.70	-1.47
Total Event Effect	-1.43	-0.02	0.35	-1.76

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Decomposition by Length of Event Window and Type of Event

	All Events			U.S. Events			China Events		
w	$R(w)$	$R^C(w)$	$R^D(w)$	$R(w)$	$R^C(w)$	$R^D(w)$	$R(w)$	$R^C(w)$	$R^D(w)$
1	-9.74	-6.57	-1.75	-8.63	-5.58	-1.31	-1.11	-0.99	-0.44
		(0.34)	(0.34)		(0.28)	(0.28)		(0.21)	(0.19)
5	-4.29	-3.36	-2.61	-3.50	-2.69	-2.13	-0.80	-0.67	-0.48
		(0.44)	(0.47)		(0.34)	(0.36)		(0.28)	(0.27)
10	-2.24	-4.50	-1.76	-5.16	-5.19	-3.25	2.92	0.68	1.49
		(0.70)	(0.59)		(0.44)	(0.51)		(0.47)	(0.40)
30	-5.74	-18.22	-0.76	-10.53	-14.94	-3.55	5.75	-2.41	2.79
		(0.97)	(0.70)		(0.61)	(0.82)		(0.60)	(0.77)

Note: Standard errors are in parentheses.

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Alternative Windows and Placebo Tests

	Average of Coefficients					
	(1)	(2)	(3)	(4)	(5)	(6)
China Importer	-0.094***	0.020	-0.076**	0.008	-0.038	-0.063***
	(0.021)	(0.024)	(0.034)	(0.038)	(0.023)	(0.017)
China Exporter	-0.027	-0.061*	-0.080	-0.074	0.014	-0.018
	(0.035)	(0.037)	(0.056)	(0.050)	(0.041)	(0.025)
China Revenue Share			-1.097***	-0.868***	0.253	0.481***
			(0.207)	(0.246)	(0.171)	(0.108)
N	137,472	137,472	60,144	60,144	80,192	100,240
w	5	5	1	1	5	5
Events	U.S.	China	U.S.	China	Other	5 Largest Declines 2017
Decomposition of Market Return in Percent						
Market Return	-3.49	-0.81	-8.63	-1.11	-4.04	-7.90
Differential Effect	-1.56	0.09	-1.31	-0.44	-0.19	-0.49
Common Effect	-2.93	-0.91	-5.58	-0.99	-7.64	-9.61
Total Event Effect	-4.50	-0.83	-6.89	-1.43	-7.83	-10.10

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Robustness Tests (3-Day Windows)

	Average of Coefficients			
	(1)	(2)	(3)	(4)
China Importer	-0.112***	-0.020	-0.005	0.031
	(0.033)	(0.038)	(0.033)	(0.028)
China Exporter	-0.086	-0.079	-0.004	-0.009
	(0.056)	(0.050)	(0.058)	(0.040)
China Revenue Share			-0.021	0.797***
			(0.272)	(0.177)
N	60,144	60,144	34,368	42,960
w	1	1	1	1
Events	U.S.	China	Other	5 Largest Declines 2017
Decomposition of Market Return in Percent				
Market Return	-8.63	-1.11	-1.71	-3.24
Differential Effect	-0.88	-0.19	-0.06	0.81
Common Effect	-5.77	-1.10	-2.90	-4.59
Total Event Effect	-6.65	-1.28	-2.95	-3.78

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Robustness Tests (Omitted Variables and Factors)

	Average of Coefficients						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
China Importer	-0.064***	-0.071***	0.036	-0.068***	0.035	-0.054**	0.025
	(0.023)	(0.022)	(0.025)	(0.022)	(0.026)	(0.021)	(0.024)
China Exporter	-0.017	-0.018	-0.061	-0.019	-0.065*	-0.014	-0.078**
	(0.035)	(0.035)	(0.037)	(0.035)	(0.037)	(0.035)	(0.036)
China Revenue Share	-0.556***	-0.633***	-0.870***	-0.557***	-0.956***	-0.608***	-0.805***
	(0.153)	(0.149)	(0.146)	(0.157)	(0.159)	(0.145)	(0.143)
Industry Protected	-0.065						
	(0.074)						
Large Company		-0.032	-0.043				
		(0.035)	(0.047)				
Non-China Revenue Share				-0.048	0.100*		
				(0.051)	(0.060)		
N	137,472	121,392	121,392	137,472	137,472	137,472	137,472
Events	U.S.	U.S.	China	U.S.	China	U.S.	China
Number of Factors	2	2	2	2	2	5	5
Decomposition of Market Return in Percent							
Market Return	-3.19	-2.24	-1.00	-3.53	-0.76	-3.51	-0.79
Differential Effect	-1.86	-2.09	-0.66	-2.33	-0.17	-1.77	-0.77
Common Effect	-2.53	-1.74	-0.59	-2.58	-0.85	-3.11	-0.35
Total Event Effect	-4.39	-3.84	-1.25	-4.92	-1.02	-4.88	-1.12

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Robustness Tests (3-Day Windows)

	Average of Coefficients						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
China Importer	-0.060*	-0.049	-0.024	-0.068*	-0.004	-0.024	-0.009
	(0.035)	(0.035)	(0.036)	(0.036)	(0.039)	(0.033)	(0.037)
China Exporter	-0.072	-0.055	-0.093*	-0.074	-0.083	-0.074	-0.082
	(0.057)	(0.057)	(0.050)	(0.057)	(0.050)	(0.055)	(0.050)
China Revenue Share	-0.967***	-1.134***	-0.956***	-1.009***	-1.000***	-1.008***	-0.896***
	(0.214)	(0.211)	(0.251)	(0.219)	(0.276)	(0.206)	(0.245)
Industry Protected	0.100						
	(0.125)						
Large Company		-0.103*	-0.138*				
		(0.054)	(0.072)				
Non-China Revenue Share				-0.068	0.101		
				(0.080)	(0.094)		
N	60,144	53,109	53,109	60,144	60,144	60,144	60,144
Events	U.S.	U.S.	China	U.S.	China	U.S.	China
Number of Factors	2	2	2	2	2	5	5
Decomposition of Market Return in Percent							
Market Return	-8.38	-6.58	-1.70	-8.63	-1.11	-8.63	-1.11
Differential Effect	-1.11	-1.12	-0.67	-1.43	-0.31	-0.90	-0.55
Common Effect	-5.46	-4.15	-1.16	-5.50	-1.08	-6.10	-0.84
Total Event Effect	-6.56	-5.27	-1.83	-6.93	-1.39	-7.00	-1.39

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Underlying Data

Date	Effects using 7-Day Event Window			Effects using 3-Day Event Window		
	Differential	Common	Total Event	Differential	Common	Total Event
2019q1	-0.19	-0.07	-0.26	-0.76	-0.23	-0.99
2019q2	-0.31	-0.07	-0.39	-0.84	-0.29	-1.14
2019q3	-0.28	-0.07	-0.35	-0.48	-0.36	-0.84
2019q4	-0.22	-0.05	-0.27	-0.37	-0.29	-0.66
2020q1	-0.11	-0.04	-0.15	0.33	-0.16	0.18
2020q2	-0.17	-0.95	-1.12	-0.00	-0.46	-0.46
2020q3	-0.10	-1.52	-1.62	-0.67	-0.69	-1.36
2020q4	-0.10	-1.47	-1.57	-0.63	-0.67	-1.30

Back

IK Regression Robustness

Back

Dep. Var.	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ IV (1)	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ IV (2)	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ IV (3)	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ IV (4)	$\Delta^4\left(\frac{I_{f,s}}{K_{f,s-4}}\right)$ OLS (5)
$\Delta^4\text{MTB}_{f,s-4}$	0.008***	0.008***	0.009***	0.008***	
	(0.002)	(0.002)	(0.002)	(0.002)	
$\Delta^4\left(\text{Cashflow}_{fs}/K_{f,s-4}\right)$	0.008***	0.008***	0.008***	0.008***	
	(0.001)	(0.001)	(0.001)	(0.001)	
$\tilde{r}^G_{f,s-4}$					-0.115
					(0.097)
$\tilde{r}^D_{f,s-4}$					0.188**
					(0.076)
$\tilde{\nu}_{f,s-4}$					0.021*
					(0.011)
$\dot{r}_{f,s-4}$					0.007***
					(0.002)
N	14,390	14,390	14,390	14,390	17,317
Factor	2	2	5	5	2
w	1	1	5	1	5
Overid J-testχ^2	2.22		12.20	2.06	
[p value]	[0.53]		[0.01]	[0.56]	
Weak IV F-test	1,636.5	6,504.7	1,634.3	1,636.3	
First Stage	$\Delta^4\text{MTB}_{f,s-4}$	$\Delta^4\text{MTB}_{f,s-4}$	$\Delta^4\text{MTB}_{f,s-4}$	$\Delta^4\text{MTB}_{f,s-4}$	
$\tilde{r}^C_{f,s-4}$	0.954*		0.589	0.526	
	(0.545)		(0.447)	(0.352)	
$\tilde{r}^D_{f,s-4}$	5.011***		3.276***	6.361***	
	(0.778)		(0.493)	(1.073)	
$\tilde{\nu}_{f,s-4}$	1.064***		1.018***	1.101***	
	(0.089)		(0.063)	(0.091)	
$\dot{r}_{f,s-4}$	0.969***		0.969***	0.969***	
	(0.012)		(0.012)	(0.012)	
$\tilde{r}_{f,s-4}$		0.973***			
		(0.012)			
First stage F-test	1,637	6,505	1,634	1,636	
[p value]	[0.00]	[0.00]	[0.00]	[0.00]	