Pricing the Global Trade Vulnerability

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Motivation: The Emergence of Trade as a New Front Line of Risk

- Over the past two decades, global trade has shifted from a period of steady growth into an era of increased risks and uncertainty.
- Trade vulnerability caused by overreliance on a small number of suppliers from a single geographical region has long been a concern for executives of multinational firms (McGee 2025, *Apple in China*).
- It was not until Trump's 2018 trade war against China, when the risk inherent in international trade begins to take center stage:
  - Trump 1.0: targeting primarily imported goods from China.
  - Covid-19: underscored the fragility of the global international trade.
  - Trump 2.0: a broad-based blow to all international trade.

This Paper: Pricing the Global Trade Vulnerability

- As trade uncertainty becomes a central force shaping corporate decisions and driving asset allocation, we look into financial markets to uncover the emerging risk factors on global trade, and importantly, to estimate the market price of trade uncertainty.
- Central to our paper is the concept of trade vulnerability:
  - Measured from the ground up using firm-level import data from S&P Panjiva.
  - Firms with more concentrated trade exposure to a small number of countries are more vulnerable to disruptions in global trade.
- Our main hypothesis:
  - Trade vulnerability elevates from a firm-level concern to a system-wide risk.
  - Firms with higher exposure to trade risk are expected to earn a higher risk premium, giving rise to a priced risk factor on global trade.

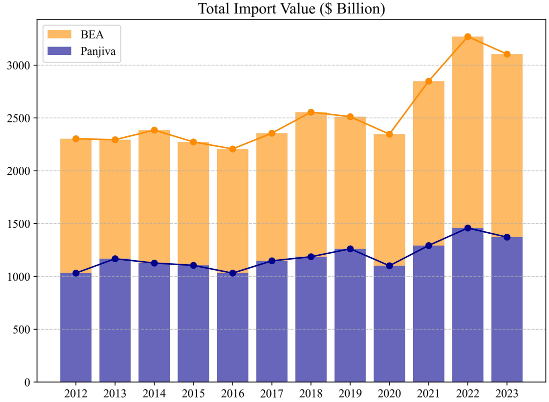
Related Literature

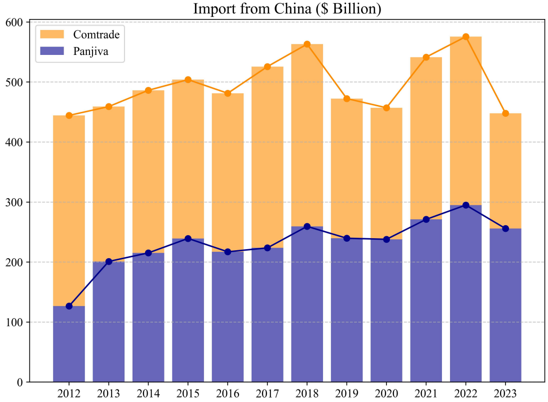
- Asset Pricing under Trade/Geopolitical Uncertainty
  - Choke-points: Dyakov & Jiang 2025.
  - Policy uncertainty measures: Baker et al. 2016.
  - Geopolitical risk: Sheng et. al. 2025 and Clayton et al. 2025.
- Supply-Chain Disruptions
  - Firm-level sourcing decisions: Grossman et al. 2023 and Ersahin et al. 2024.
  - Economic losses due to concentrated sourcing: Ahn & Tan 2025.
  - On China dependence: Aral et al. 2025 and Alfaro & Chor 2023.
  - Macro implications: Carvalho et al. 2021 and Acemoglu & Tahbaz-Salehi 2025.
  - Alternative ways to mitigate disruptions: via political connection Cen et al. 2024 or M&A Cen et al. 2025.

Part I: Data

- S&P Panjiva Bill of Lading Data
  - The Panjiva dataset is compiled from U.S. Customs, shipping companies, and digitized paper bills of lading collected by S&P Global.
  - This highly granular dataset includes both private and public U.S. firms, containing detailed shipment-level information (e.g., shipment value, supplier, cargo description, TEU, and date).
- Public Firms Sample
  - We extract Panjiva import shipment records from 2012–2023 and merge U.S. consignees with Compustat public firms using S&P Global Company IDs.
  - The final sample includes 1,840 unique firms, with a cumulative shipment value of $469.9 billion.
  - The average annual import value is approximately $44 million per firm.

Total Import Value: Panjiva vs BEA





Summary Statistics

	Mean	Std	P1	P25	Median	P75	P99
Import amount							
Import value ($ thousand)	44,390	247,911	0.85	151	1,567	11,976	723,289
Import/revenue ratio (%)	2.25	14.41	0.00	0.01	0.11	0.81	34.68
Import from number of							
Countries	5.62	6.86	1.00	1.15	3.00	6.92	35.33
Suppliers	19.94	60.91	1.00	1.92	4.92	15.71	229.80
HS2 Goods	5.94	7.20	1.00	1.25	3.17	7.42	35.40
Import ratio (%)							
Asia	75.05	34.26	0.20	55.06	95.89	100	100
China	42.03	36.84	0.03	7.11	31.44	78.17	100
Europe	43.58	40.07	0.02	4.44	30.66	90.52	100
North America	22.88	34.49	0.00	0.40	3.33	31.42	100
South America	17.42	29.35	0.00	0.32	2.63	18.98	100
Africa	12.20	25.30	0.00	0.20	1.30	8.12	97.81
Oceania	14.18	28.61	0.00	0.10	0.95	8.56	100

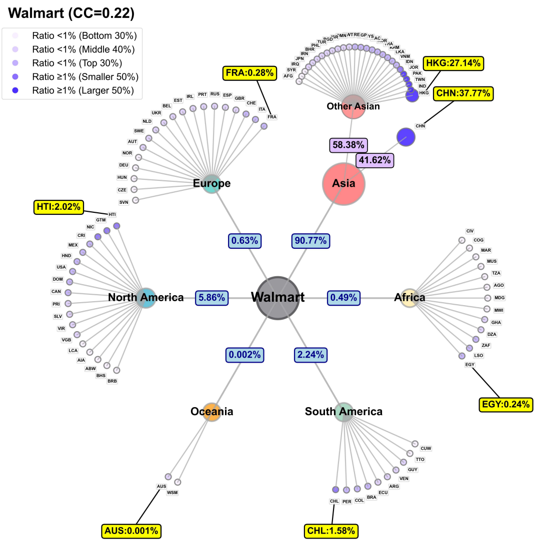
Part II: Measure of Trade Vulnerability

- Central to our analysis is the measure of Country Concentration (CC).
- For firm i in year t, CC_{it} is obtained by applying Herfindahl index to country-level shares of import

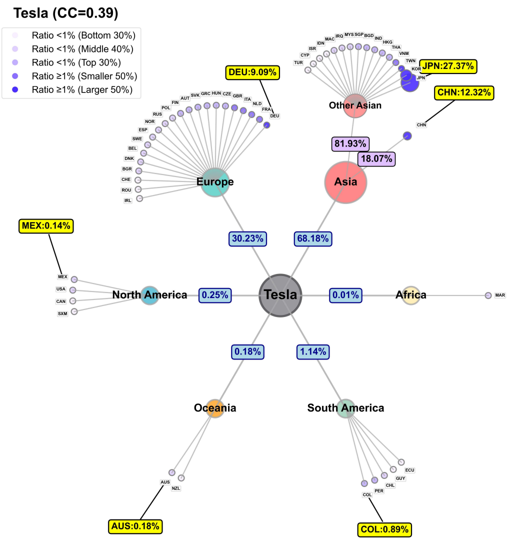
$$\text{CC}_{it} = \sum_{c} \left(\frac{\text{Import Value}_{itc}}{\sum_c \text{Import Value}_{itc}} \right)^2$$

- The largest value of CC is 1 (when sourcing from one single country), while the lower bound of CC is the inverse of the number of sourcing countries.
- With import exposure concentrated to a small number of countries, high-CC firms are potentially more vulnerable to trade disruptions (e.g., concentrated exposure to China during the US-China trade war). By contrast, low-CC firms are better diversified and less vulnerable.

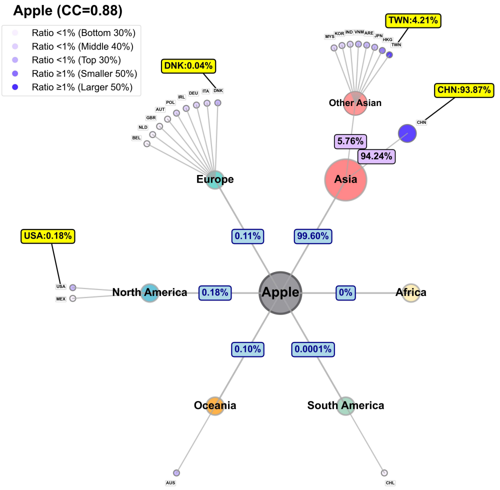
Walmart's Import Network



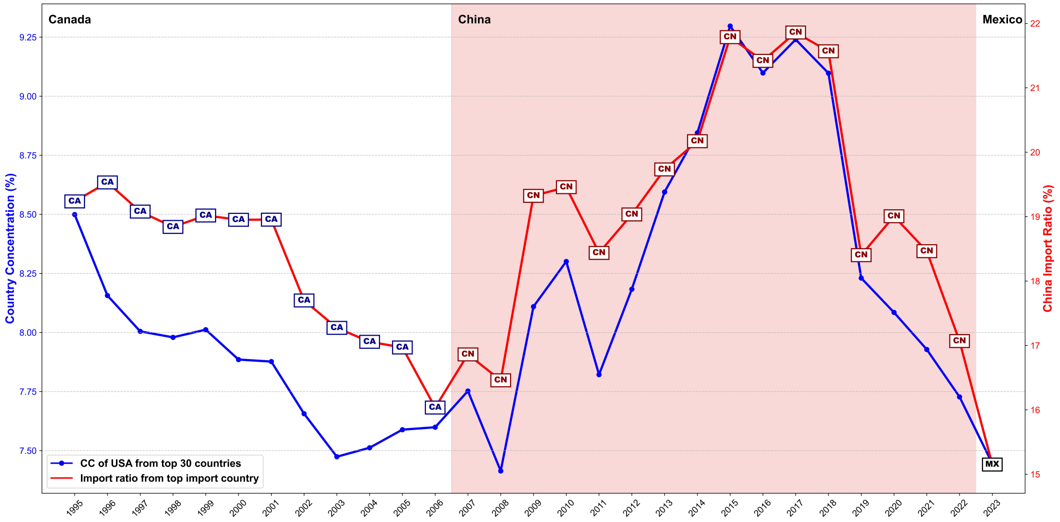
Telsa's Import Network



Apple's Import Network



USA's Country Concentration and China Exposure



Part III: Pricing the Global Trade Vulnerability

- We use the firm-level country concentration to sort stocks into portfolios of high (P3), medium (P2), and low (P1) vulnerability.
  - Our trade risk factor = P3 (high-CC) - P0 (no trade exposure).
  - The market price of trade risk = the risk premium of the trade risk factor, controlling for existing risk factors.
  - Analyze the drivers of CC-sorted portfolios.
- We also examine the pricing results using alternative measures of trade vulnerability
  - Supplier and goods concentration
  - Numbers of sourcing countries, suppliers, and goods.
  - Import-to-revenue ratio and import dollar volume
  - China exposure

Portfolio Construction

- To take into account of the industry variation in import intensity, we demean firm-level CC by its industry-year average:

$$\mathsf{CC}_{i,t}^{\mathsf{demean}} = \mathsf{CC}_{i,t} - \overline{\mathsf{CC}}_{I(i),t}\ ,$$

  where $I(i)$ is firm-i's Fama–French 48 industry and $\overline{\mathsf{CC}}_{I,t}$ is the average CC of industry I in year t.
- We sort stocks into portfolios using their industry-demeaned CC from the previous shipping year
  - To avoid look-ahead bias, we follow the UN Comtrade data release policy, which publishes country-level import/export data for the prior calendar year in June.
  - We then merge these shipping data with fiscal year revenue data to calculate the import/revenue ratio, and exclude firms with negligible ratios.
- Portfolio formation begins at the end of December 2013, excluding firms with stock prices less than $5, and is rebalanced monthly.

Summary Statistics of the CC-Sorted Portfolios

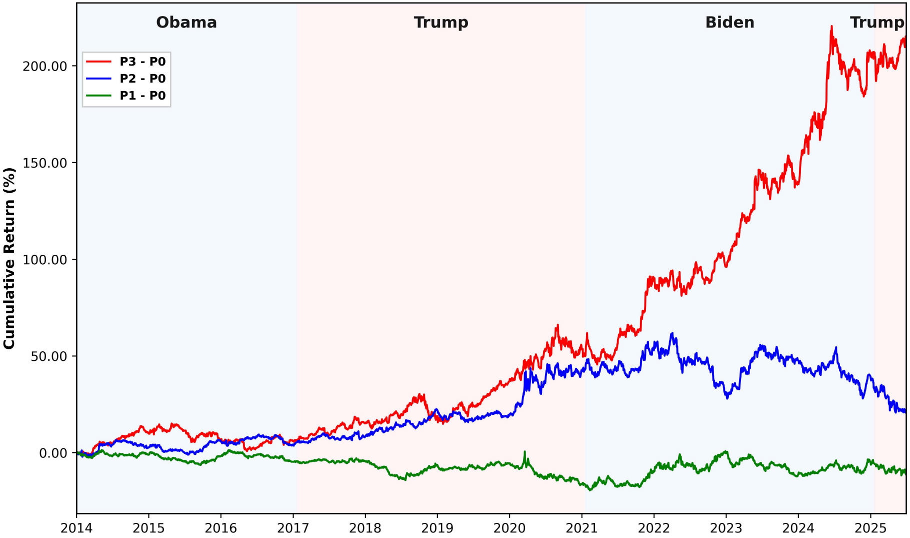
	Mean				Median			
	P1	P2	P3	P0	P1	P2	P3	P0
Country Concentration (industry demeaned)	-0.31	-0.05	0.28		-0.29	-0.06	0.27	
Country Concentration	0.31	0.55	0.91		0.30	0.53	0.97	
Supplier Concentration	0.22	0.41	0.78		0.21	0.41	0.88	
HS2 Goods Concentration	0.51	0.64	0.83		0.47	0.63	0.95	
Number of Countries	12.20	7.11	2.99		9.24	5.13	2.00	
Number of Suppliers	49.05	28.22	7.58		20.69	10.20	2.90	
Number of HS2 Goods	11.45	7.67	3.80		8.82	5.38	2.13	
Import Value ($ million)	101	72	28		10	5	1	
Import/Revenue Ratio (%)	1.65	2.00	1.79		0.34	0.24	0.11	
Number of Firms	175	195	229	2190				
Market Cap ($ million)	23,555	23,076	18,406	6,517	3,909	2,418	1,638	1,074
Revenue ($ million)	13,910	9,170	6,730	3,887	3,279	2,026	1,197	582
ROA (%)	5.22	4.48	2.38	-2.24	5.45	5.01	4.36	1.51
Operating Margin (%)	10.47	7.95	-22.91	-98.46	9.95	9.35	8.58	11.91

Empirical Performance of the CC-Sorted Portfolios

$$R_t^i - r_f = \alpha^{\text{FF5}} + \beta^{\text{MKT}}\left(R_t^{\text{MKT}} - r_f\right) + \beta^{\text{SMB}} R_t^{\text{SMB}} + \beta^{\text{HML}} R_t^{\text{HML}} + \beta^{\text{RMW}} R_t^{\text{RMW}} + \beta^{\text{CMA}} R_t^{\text{CMA}} + \epsilon_t^i$$

	No Trade	**CC-Sorted Portfolios**			**CCTF Factors**	
	P0	P1	P2	P3	P3 - P0	P3 - P1
Excess ret (%)	0.84	0.80	1.04	1.71	0.87	0.91
	[2.78]	[3.02]	[2.83]	[4.51]	[3.76]	[3.49]
FF5 alpha (%)	-0.03	-0.12	0.00	0.52	0.55	0.64
	[-0.46]	[-1.12]	[-0.01]	[3.25]	[2.88]	[2.87]
MKT beta	0.98	0.89	1.03	1.09	0.11	0.20
	[88.62]	[32.11]	[24.58]	[28.40]	[2.48]	[3.70]
SMB beta	0.08	-0.03	-0.06	-0.04	-0.11	-0.01
	[3.13]	[-0.80]	[-1.03]	[-0.48]	[-1.40]	[-0.06]
HML beta	0.12	0.10	-0.22	-0.19	-0.31	-0.29
	[4.46]	[1.86]	[-3.64]	[-2.45]	[-3.53]	[-2.42]
RMW beta	-0.14	0.22	-0.04	0.26	0.39	0.04
	[-3.99]	[3.26]	[-0.48]	[2.70]	[3.34]	[0.31]
CMA beta	-0.09	0.15	0.01	-0.16	-0.06	-0.31
	[-1.88]	[1.58]	[0.08]	[-1.10]	[-0.36]	[-1.47]

The Emergence of a Trade Risk Factor



Alternative Measures of Trade Vulnerability

	Fama-French 5-Factor Alpha (%)					
	No Trade	**Sorted Portfolios**			**Long/Short**	
Alternative Measures	P0	P1	P2	P3	P3 - P0	P3 - P1
Supplier Concentration (SC)	-0.03	0.05	-0.11	0.42	0.44	0.36
	[-0.46]	[0.57]	[-0.65]	[2.31]	[2.08]	[1.81]
HS2 Goods Concentration (GC)	-0.03	0.08	-0.04	0.33	0.36	0.25
	[-0.46]	[0.79]	[-0.24]	[2.05]	[2.01]	[1.43]
1/Number of Countries (1/NC)	-0.03	0.19	-0.32	0.54	0.57	0.36
	[-0.46]	[1.89]	[-2.05]	[2.18]	[2.13]	[1.26]
1/Number of Suppliers (1/NS)	-0.03	0.26	-0.34	0.42	0.44	0.16
	[-0.46]	[2.51]	[-3.07]	[1.81]	[1.81]	[0.61]
1/Number of HS2 Goods (1/NG)	-0.03	0.18	-0.22	0.22	0.24	0.03
	[-0.46]	[2.12]	[-1.44]	[0.92]	[0.95]	[0.13]
Import/Revenue (Import)	-0.03	0.24	0.13	-0.15	-0.12	-0.39
	[-0.46]	[1.44]	[1.30]	[-1.02]	[-0.72]	[-1.51]
China Ratio (China)	-0.03	0.11	-0.07	0.22	0.25	0.11
	[-0.46]	[0.52]	[-0.60]	[1.55]	[1.41]	[0.40]

A Two-Factor Model with Country Concentration Trade Factor (CCTF)

- We construct the country concentration trade factor (CCTF) via

$$R_t^{\text{CCTF}} = R_t^{\text{P3}} - R_t^{\text{P0}}\,,$$

where P3 is the high-CC portfolio and P0 is the portfolio with no trade exposure.

- Our two-factor model:

$$R_t^i - r_f = \alpha + \beta^{\text{MKT}}\left(R_t^{\text{MKT}} - r_f\right) + \beta^{\text{CCTF}} R_t^{\text{CCTF}} + \epsilon_t^i\,.$$

- Applied to the long/short portfolios constructed from the alternative measures:

Alternative Measures	SC	GC	1/NC	1/NS	1/NG	Import	China
alpha (%)	0.00	0.15	0.08	0.01	-0.14	-0.12	-0.09
	[0.00]	[1.18]	[0.53]	[0.08]	[-0.72]	[-0.66]	[-0.60]
MKT beta	-0.01	-0.04	0.05	0.11	0.12	-0.11	-0.01
	[-0.15]	[-1.04]	[1.02]	[2.04]	[2.24]	[-2.86]	[-0.26]
CCTF beta	0.69	0.37	0.94	0.72	0.71	0.17	0.78
	[6.38]	[3.15]	[9.85]	[5.51]	[5.96]	[2.19]	[7.72]

Part IV: Understanding the Drivers of the Trade Risk Factors

- An important driver of the risk premium is concentrated China exposure.
- Industry exposures – a close connection to the tech sector.
- When is the high-CC portfolio more volatile?
- The evolving nature of trade vulnerability.

Concentrated China Exposure as a Key Driver

	Country Concentration					
	P1 (low)		P2		P3 (high)	
	High CHN	Low CHN	High CHN	Low CHN	High CHN	Low CHN
Ex Ret (%)	0.84	0.80	1.28	0.74	$\boxed{2.03}$	0.93
	[2.99]	[3.01]	[2.81]	[2.29]	$\boxed{[4.41]}$	[3.44]
alpha (%)	-0.13	-0.09	0.05	-0.09	$\boxed{0.68}$	0.18
	[-0.94]	[-0.81]	[0.28]	[-0.42]	$\boxed{[2.91]}$	[0.83]
MKT beta	0.99	0.85	1.18	0.86	1.17	0.84
	[25.57]	[29.02]	[18.07]	[25.39]	[18.50]	[16.17]
SMB beta	0.05	-0.06	-0.15	0.05	-0.14	0.27
	[0.77]	[-1.43]	[-1.45]	[0.77]	[-1.24]	[3.62]
HML beta	0.10	0.10	-0.41	0.08	-0.35	0.13
	[1.42]	[2.00]	[-4.41]	[1.11]	[-2.91]	[1.19]
RMW beta	0.19	0.24	-0.08	0.06	0.34	0.09
	[1.94]	[3.49]	[-0.58]	[0.95]	[2.47]	[0.95]
CMA beta	0.12	0.15	0.01	0.02	-0.18	0.04
	[1.29]	[1.57]	[0.07]	[0.12]	[-0.87]	[0.28]

Industry Exposures of the CC-Sorted Portfolios

$$R_t^{\mathrm{P}i} - r_f = \alpha + \beta^{\mathrm{MKT}}\left(R_t^{\mathrm{MKT}} - r_f\right) + \beta^{\mathrm{Industry}} R_t^{\mathrm{Industry}} + \epsilon_t^i$$

Fama-French 48 Industry	Ranking	P0	P1	P2	P3
(7) Chips	Top 10	-0.16	-0.15	**0.14**	**0.47**
(20) BusSv	Top 10	-0.09	-0.30	**0.26**	**0.25**
(2) Rtail	Top 10	-0.08	-0.11	**0.32**	**0.17**
(4) Comps	Top 10	-0.04	0.09	-0.08	0.09
(1) Autos	Top 10	-0.02	-0.05	**0.09**	0.05
(39) Fun	Top 10	0.02	-0.09	-0.01	0.02
(47) Coal	Top 10	**0.01**	0.01	-0.04	-0.01
(45) FabPr	Top 10	**0.02**	0.00	-0.02	-0.03
(42) Gold	Top 10	-0.01	0.01	**0.04**	-0.03
(27) Mines	Top 10	0.01	0.02	-0.00	-0.04
(8) Food	Bottom 10	0.02	**0.21**	-0.10	-0.18
(9) MedEq	Bottom 10	**0.06**	0.06	0.02	-0.18
(21) Paper	Bottom 10	0.02	**0.26**	-0.10	-0.20
(14) Trans	Bottom 10	**0.08**	**0.11**	-0.08	-0.21
(22) Meals	Bottom 10	**0.06**	**0.11**	-0.07	-0.22
(15) Chems	Bottom 10	**0.08**	**0.17**	-0.06	-0.24
(10) Whlsl	Bottom 10	**0.15**	**0.26**	-0.27	-0.25
(40) Insur	Bottom 10	**0.13**	**0.19**	-0.18	-0.25
(16) Banks	Bottom 10	**0.15**	**0.08**	-0.28	-0.26
(43) Fin	Bottom 10	**0.17**	0.04	-0.24	-0.27

Ranking: Top 10 / Bottom 10

Industry Beta (color scale: −0.4, −0.2, 0.0, 0.2, 0.4)

Industry Exposures of CC×China-Sorted Portfolios

Fama-French 48 Industry

		P1 High China	P1 Low China	P2 High China	P2 Low China	P3 High China	P3 Low China
7	Chips	-0.19	-0.13	**0.30**	-0.08	**0.74**	-0.17
20	BusSv	-0.37	-0.28	**0.48**	-0.10	**0.58**	-0.43
2	Rtail	-0.05	-0.14	**0.66**	-0.13	**0.32**	-0.28
4	Comps	0.09	0.08	-0.05	-0.03	0.18	-0.02
1	Autos	-0.04	-0.06	**0.14**	-0.03	**0.10**	-0.05
39	Fun	-0.08	-0.09	0.04	-0.09	0.08	-0.09
47	Coal	0.01	0.01	-0.06	0.01	-0.04	**0.06**
45	FabPr	0.03	-0.01	-0.05	0.00	-0.05	0.03
3	Clths	0.06	0.06	-0.04	-0.06	-0.05	-0.02
42	Gold	0.01	0.02	0.01	**0.06**	-0.06	0.02
32	PerSv	**0.22**	0.04	-0.19	-0.05	-0.33	**0.17**
14	Trans	**0.17**	0.08	-0.22	**0.12**	-0.34	0.11
21	Paper	**0.26**	**0.26**	-0.23	0.11	-0.35	**0.19**
17	Other	**0.27**	**0.26**	-0.29	0.06	-0.35	0.15
26	Telcm	0.06	0.06	-0.34	0.00	-0.36	**0.22**
43	Fin	**0.12**	0.02	-0.39	-0.05	-0.41	0.09
16	Banks	**0.12**	0.06	-0.45	-0.00	-0.42	**0.13**
15	Chems	**0.26**	**0.14**	-0.26	**0.25**	-0.44	**0.22**
40	Insur	**0.22**	**0.17**	-0.29	0.04	-0.52	**0.27**
10	Whlsl	**0.39**	**0.21**	-0.50	**0.15**	-0.54	**0.40**

Ranking
- 🟥 Top 10
- 🟦 Bottom 10

Industry Beta: 0.6, 0.4, 0.2, 0.0, −0.2, −0.4, −0.6

Controlling for Industry Exposure: Rescale by Universal Industry Weights

- For each portfolio $p \in \{P0, P1, P2, P3\}$, we form 48 industry portfolios.
- To even out the industry distribution across p, we further rescale the relative weights across the 48 industries by the industry weights from the entire universe of stocks.

	CC-Sorted Portfolios				Risk Factors	
	P0	P1	P2	P3	P3 - P0	P3 - P1
Excess return	0.86 [2.74]	0.86 [2.85]	1.04 [3.09]	1.26 [4.02]	0.42 [3.96]	0.41 [3.19]
α^{CAPM}	-0.15 [-2.43]	-0.10 [-1.05]	0.05 [0.39]	0.28 [2.99]	0.46 [4.16]	0.39 [3.42]
α^{FF5}	-0.04 [-0.85]	-0.06 [-0.76]	0.15 [1.25]	0.31 [3.79]	0.38 [3.98]	0.38 [3.12]

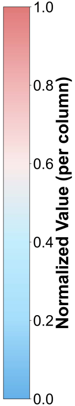
Controlling for Industry Exposure: Long/Short within Industry

- Sort stocks within each of the Fama-French 12 industries by their CC.
- Industries with fewer than 20 firms are dropped. Utilities, Telecom, Energy, Money.

	CC-Sorted Portfolios				Risk Factors	
	P0	P1	P2	P3	P3 - P0	P3 - P1
Excess return	1.03 [2.97]	1.03 [3.40]	1.00 [3.31]	1.70 [5.01]	0.67 [3.93]	0.67 [3.07]
α^{CAPM}	-0.01 [-0.06]	0.13 [1.13]	0.05 [0.39]	0.68 [4.72]	0.69 [4.16]	0.56 [2.79]
α^{FF5}	0.07 [0.80]	0.08 [0.75]	-0.01 [-0.10]	0.63 [4.36]	0.56 [3.51]	0.55 [2.71]

The Industry-Level Results

	Total Import	CHN Import	CHN Ratio	Industry CC	P3-P0	P3-P1
1 Manuf 4	$6,623M	$1,030M	16%	0.09	0.00%	0.01%
2 NoDur 5	$6,427M	$764M	12%	0.08	-0.18%	-0.04%
3 Shops 2	$6,096M	$2,153M	35%	0.18	0.13%	0.04%
4 BusEq 1	$5,944M	$2,799M	47%	0.27	**1.06%**	**1.22%**
5 Durbl 3	$5,052M	$1,068M	21%	0.22	-0.16%	-0.13%
6 Hlth 7	$1,944M	$349M	18%	0.21	**0.45%**	0.11%
7 Other 6	$1,898M	$455M	24%	0.20	0.40%	0.44%
8 Chems 8	$1,340M	$179M	13%	0.10	**0.77%**	0.08%



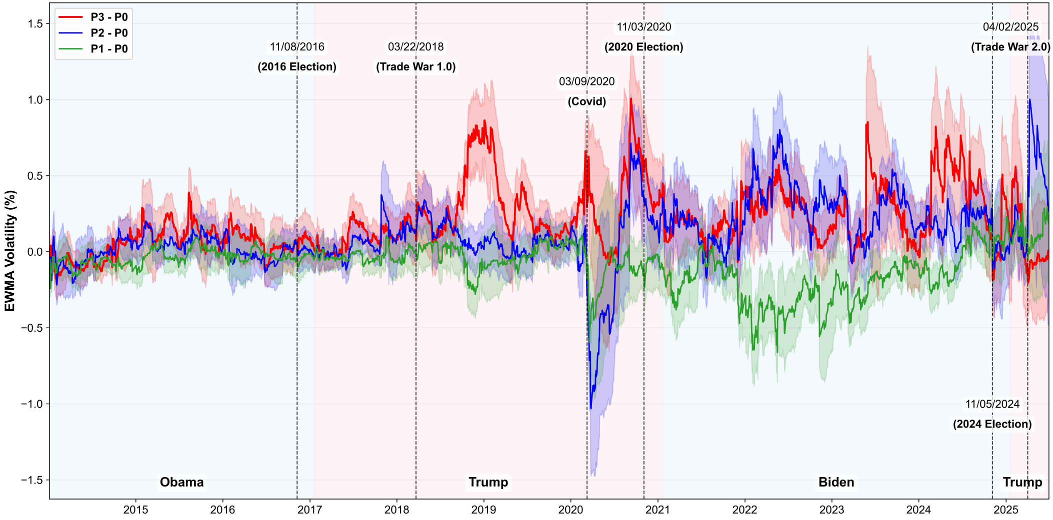
Robustness Against Tech Exposure

	With Industry Control						Without Industry Control					
	CC-Sorted Portfolios				Risk Factors		CC-Sorted Portfolios				Risk Factors	
	P0	P1	P2	P3	P3 - P0	P3 - P1	P0	P1	P2	P3	P3 - P0	P3 - P1
alpha	-0.12	-0.01	0.07	0.28	0.40	0.29	-0.08	0.06	-0.05	0.52	0.60	0.46
	[-1.92]	[-0.18]	[0.54]	[3.05]	[3.49]	[2.47]	[-1.11]	[0.71]	[-0.33]	[3.00]	[2.81]	[2.44]
MKT beta	1.04	1	1.02	1.01	-0.03	0.01	1.01	0.87	1.02	1.10	0.09	0.23
	[66.06]	[30.46]	[44.59]	[30.44]	[-0.99]	[0.24]	[75.67]	[37.50]	[30.61]	[31.31]	[2.10]	[4.99]
NASDAQ$^{\perp}$ beta	-0.18	-0.54	-0.11	-0.02	0.17	0.52	-0.27	-0.59	0.57	0.76	1.03	1.35
	[-3.10]	[-7.29]	[-1.18]	[-0.27]	[1.81]	[4.84]	[-3.93]	[-5.83]	[4.19]	[6.70]	[6.75]	[8.14]
alpha	-0.08	0.04	0.1	0.3	0.38	0.26	-0.03	0.09	-0.12	0.43	0.46	0.33
	[-1.25]	[0.58]	[0.73]	[3.39]	[3.31]	[2.29]	[-0.49]	[1.02]	[-0.88]	[2.62]	[2.36]	[1.94]
MKT beta	1.04	1	1.02	1.01	-0.03	0.01	1.01	0.87	1.02	1.10	0.09	0.23
	[76.40]	[28.83]	[46.50]	[31.65]	[-0.96]	[0.23]	[93.12]	[35.51]	[31.67]	[33.15]	[2.33]	[4.96]
QQQ$^{\perp}$ beta	-0.2	-0.39	-0.13	-0.06	0.15	0.33	-0.25	-0.37	0.47	0.61	0.86	0.98
	[-5.70]	[-6.23]	[-1.65]	[-1.19]	[2.51]	[3.96]	[-5.72]	[-4.75]	[4.78]	[6.71]	[7.67]	[7.31]
alpha	-0.05	0	0.12	0.24	0.29	0.24	0.00	0.08	-0.06	0.28	0.28	0.20
	[-0.96]	[0.00]	[0.94]	[2.46]	[2.80]	[2.24]	[-0.01]	[0.70]	[-0.34]	[2.27]	[2.28]	[1.20]
MKT beta	1.04	1	1.02	1.01	-0.03	0.01	1.01	0.87	1.02	1.10	0.09	0.23
	[77.90]	[30.64]	[45.03]	[28.88]	[-0.98]	[0.24]	[94.96]	[37.09]	[25.25]	[39.37]	[2.83]	[5.72]
Chips$^{\perp}$ beta	-0.12	-0.13	-0.09	0.05	0.18	0.18	-0.16	-0.15	0.14	0.47	0.63	0.62
	[-5.17]	[-3.97]	[-2.59]	[2.52]	[6.39]	[4.70]	[-5.66]	[-3.77]	[2.72]	[14.79]	[14.20]	[10.00]

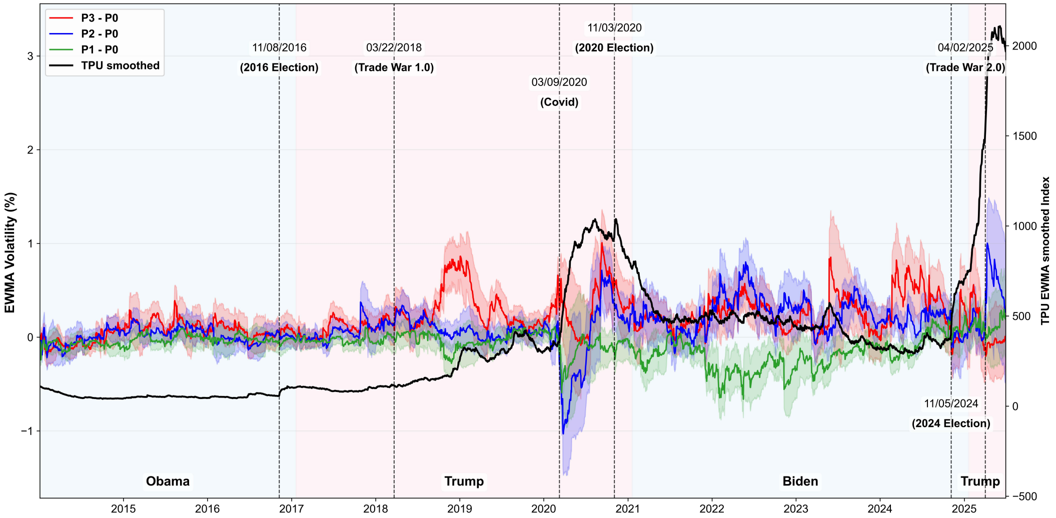
Can CCTF Explain the Tech Performance?

	NASDAQ	QQQ	SP500TECH	Comps	Chips	BusSv	Rtail	Autos
CAPM: $R_t^i - r_f = \alpha + \beta^{\text{MKT}} (R_t^{\text{MKT}} - r_f) + \epsilon_t^i$								
alpha (%)	0.17 [1.06]	0.37 [1.76]	0.51 [2.52]	0.11 [0.56]	0.80 [2.76]	0.32 [1.38]	0.16 [0.64]	-0.02 [-0.04]
MKT beta	1.10 [30.53]	1.07 [20.78]	1.10 [20.59]	1.04 [14.77]	1.22 [16.77]	1.05 [26.94]	1.01 [16.99]	1.80 [8.75]
Add Industry-Controlled CCTF: $R_t^i - r_f = \alpha + \beta^{\text{MKT}} (R_t^{\text{MKT}} - r_f) + \beta^{\text{CCTF}} R_t^{\text{CCTF}} + \epsilon_t^i$								
alpha (%)	0.08 [0.46]	0.23 [1.04]	0.21 [0.96]	0.12 [0.66]	0.27 [0.98]	0.29 [1.30]	0.11 [0.40]	-0.49 [-0.81]
MKT beta	1.1 [29.24]	1.08 [19.84]	1.12 [19.64]	1.04 [14.55]	1.25 [16.40]	1.05 [26.85]	1.01 [17.13]	1.83 [8.27]
CCTF beta	0.21 [1.78]	0.31 [2.50]	0.7 [6.15]	-0.01 [-0.07]	1.21 [6.36]	0.05 [0.48]	0.1 [0.71]	1.07 [1.28]
Add CCTF: $R_t^i - r_f = \alpha + \beta^{\text{MKT}} (R_t^{\text{MKT}} - r_f) + \beta^{\text{CCTF}} R_t^{\text{CCTF}} + \epsilon_t^i$								
alpha (%)	-0.09 [-0.64]	0.01 [0.06]	-0.02 [-0.16]	0.01 [0.07]	-0.05 [-0.33]	0.14 [0.67]	-0.01 [-0.02]	-0.52 [-0.90]
MKT beta	1.07 [38.07]	1.03 [27.12]	1.03 [35.35]	1.02 [15.22]	1.12 [26.09]	1.02 [25.84]	0.99 [16.88]	1.74 [8.52]
CCTF beta	0.33 [6.89]	0.46 [6.91]	0.69 [13.18]	0.13 [1.21]	1.09 [12.78]	0.23 [3.18]	0.21 [2.35]	0.63 [1.74]

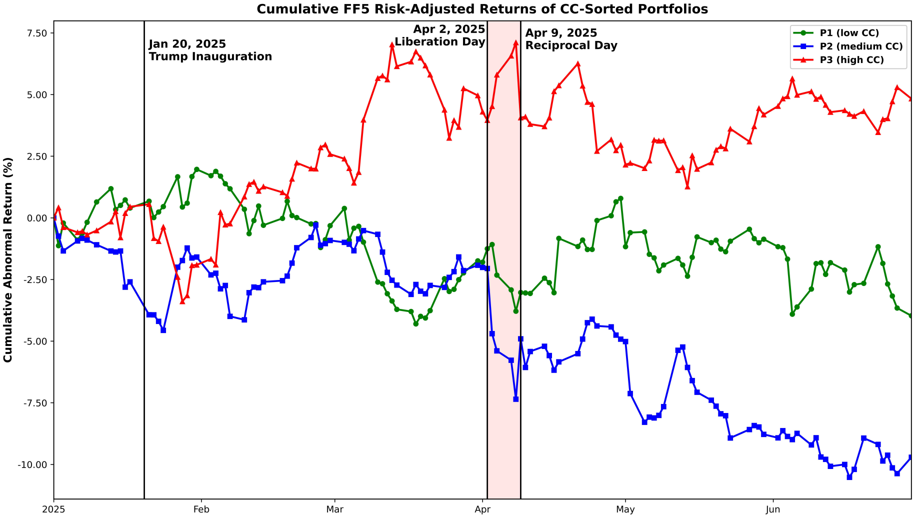
When is the High-CC Portfolios More Volatile?



When is the High-CC Portfolios More Volatile?



The Evolving Nature of Trade Vulnerability



Conclusions

- We document the emergence of a priced global trade risk factor
  - Central to our estimation is the concept of trade vulnerability, measured by the firm-level country concentration using granular bill-of-landing data.
  - High-concentration firms, more vulnerable to disruptions in global trade, demand a significantly higher risk premium.
- Triggered by the 2018 US-China tariff war and exacerbated by Covid-19 supply chain disruptions, concentrated exposure to China is a key driver to the estimated risk premium.
- Pushing beyond China, the broad-based Liberation Day tariffs hit the pricing of medium-concentration firms the hardest, reflecting the evolving nature of trade vulnerability.