Pricing the Global Trade Vulnerability

Jun Pan

Shanghai Advanced Institute of Finance (SAIF)
Shanghai Jiao Tong University

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Bank for International Settlements
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Joint work with Jiatao Liu (Xi'an Jiaotong-Liverpool University)

Vulnerability Inherent in Efficiency-Driven Globalization

- Building on decades of postwar trade liberalization, globalization entered a period of unprecedented expansion and deepening integration beginning in the 1990s.
- This phase of globalization gave rise to geographically concentrated production networks that enhanced efficiency but exposed firms to common geopolitical risks.
- As the global trade environment shifted toward heightened uncertainty, this previously underappreciated vulnerability emerged as a source of systematic risk:
  - Trump 1.0 in 2018 targeted primarily imported goods from China.
  - Covid-19 in 2020 underscored the fragility of the global trade.
  - Trump 2.0 in 2025 was a broad-based blow to all trade partners.
  - ...
- This emerging trade vulnerability is shifting the design of global supply chains from economic efficiency toward resilience against geopolitics.

This Paper: Emerging Trade Vulnerability as a Priced Risk Factor

- As increasing trade uncertainty reshapes corporate decisions and asset pricing, we turn to financial markets to uncover the emerging global trade risk factor and, importantly, estimate its risk premium.
- 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 concentrated trade exposure to a small number of countries – more vulnerable to disruptions in global trade.
- Our main hypothesis:
  - Trade vulnerability elevates from a firm-level concern to a system-wide risk.
  - It becomes a priced 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 and Tahbaz-Salehi 2025.
  - Mitigating disruptions via political connection Cen et al. 2024 and via M&A Cen et al. 2025.

Part I

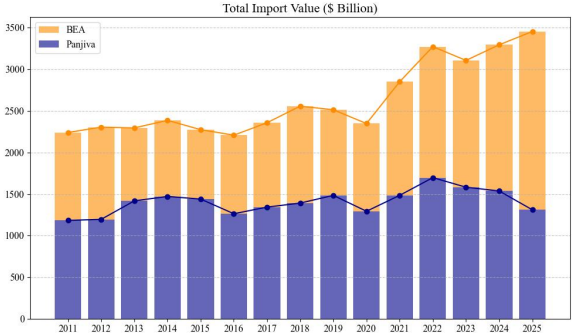
Measuring Global Trade Vulnerability

Data

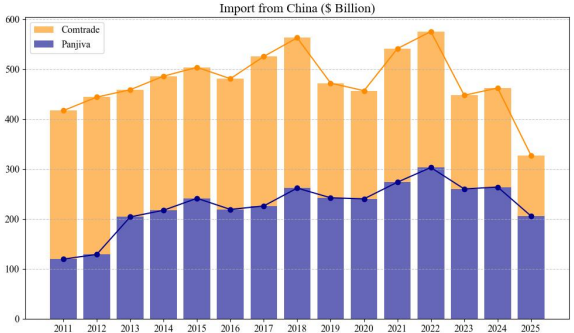
- S&P Panjiva Bill of Lading Data
  - The Panjiva dataset is compiled from U.S. Customs, shipping companies, and digitized paper bills of lading collected by S&P Global.
  - This highly granular dataset includes both private and public U.S. firms, containing detailed shipment-level information (e.g., shipment value, supplier, cargo description, TEU, and date).
- Public Firms Sample
  - We extract Panjiva import shipment records from 2011–2025 and merge U.S. consignees with Compustat public firms using S&P Global UltimateParent ID.
  - The final sample includes 3,381 unique firms, with a cumulative shipment value of $3,254 billion.
  - The average annual import value is approximately $134 million per firm.

Total Import Value: Panjiva vs BEA

Total Import Value ($ Billion)



Import from China ($ Billion)



Summary Statistics

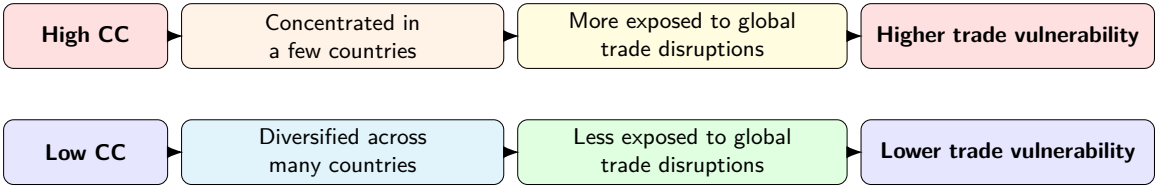
	Mean	Std	P1	P25	Median	P75	P99
Import amount							
Import value ($ millions)	134	1085	0.00	0.26	3.15	25.74	2309
Import/revenue ratio (%)	3.08	21.64	0.00	0.02	0.23	1.35	42.36
Import from number of							
Countries	7.71	8.91	1.00	2.00	4.40	10.33	42.81
Suppliers	30.89	80.29	1.00	2.22	7.83	27.80	321.17
HS2 Goods	8.28	9.40	1.00	2.00	4.93	11.27	43.95
Import ratio (%)							
Asia	70.62	35.40	0.13	42.51	90.29	100	100
China	37.92	35.55	0.01	5.50	25.89	67.39	100
Europe	39.59	37.88	0.02	4.28	25.33	77.71	100
North America	19.05	31.04	0.00	0.36	2.60	21.10	100
South America	13.86	25.35	0.00	0.29	2.10	12.29	99.74
Africa	8.79	20.07	0.00	0.13	0.92	5.74	97.47
Oceania	8.23	21.25	0.00	0.06	0.44	3.04	99.92

Measure of Trade Vulnerability

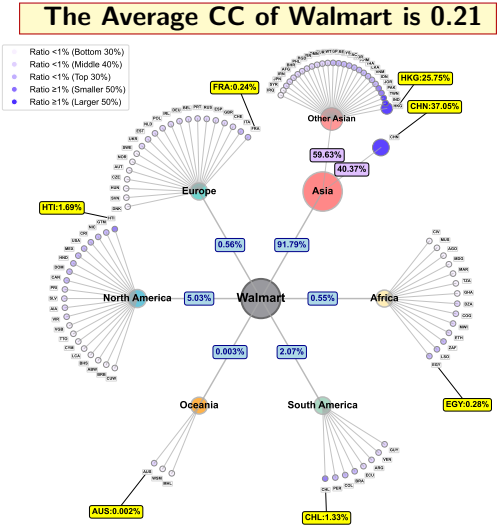
- Central to our analysis is **Country Concentration (CC)**.
- For firm i in year t, CC_{it} is the Herfindahl index of country-level import shares:

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

- $\text{CC}_{it} = 1$ when a firm sources from only one country; the lower bound is the inverse of the number of sourcing countries.



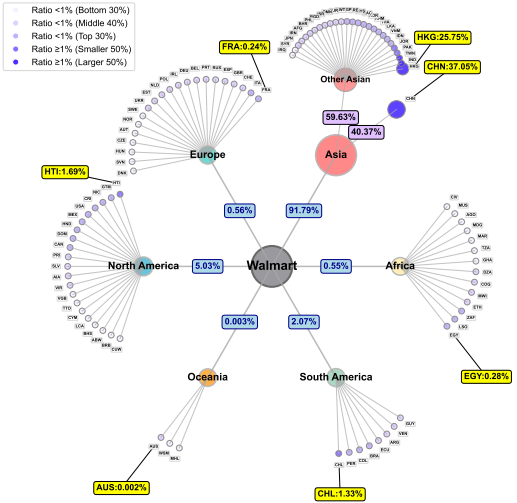
Walmart's Import Network and Top 20 Suppliers



S&P Panjiva (2011-2025)

Walmart's Import Network and Top 20 Suppliers

The Average CC of Walmart is 0.21



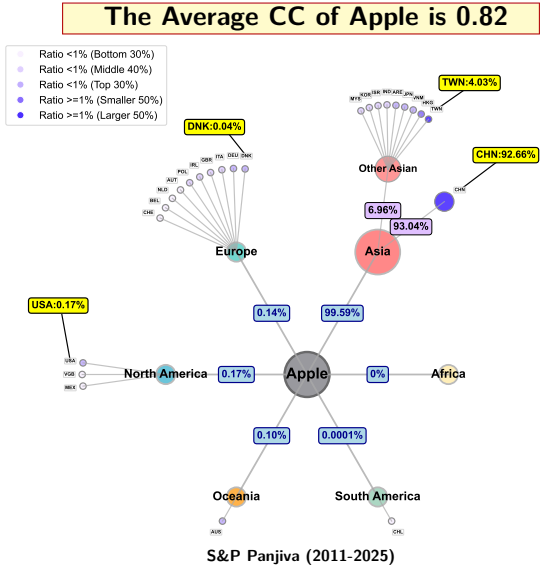
S&P Panjiva (2011-2025)

Walmart: Top Suppliers by Ranking

Rank	Supplier	Country	%Cost
1	MCK	US	7.73%
2	PG	US	2.62%
3	PEP	US	2.46%
4	TSN	US	1.93%
5	Nestle	Switzerland	1.53%
6	BRK/A	US	1.64%
7	Kraft Heinz	US	0.99%
8	ULVR	UK	0.95%
9	GIS	US	0.83%
10	CAG	US	0.65%
11	Grupo Bimbo	Mexico	0.63%
12	SJM	US	0.56%
13	KDP	US	0.50%
14	KMB	US	0.49%
15	KO	US	0.48%
16	Smithfield	US	0.44%
17	AB InBev	Belgium	0.40%
18	CL	US	0.42%
19	Arca Continental	Mexico	0.41%
20	CPB	US	0.41%
China Total			**0.00%**

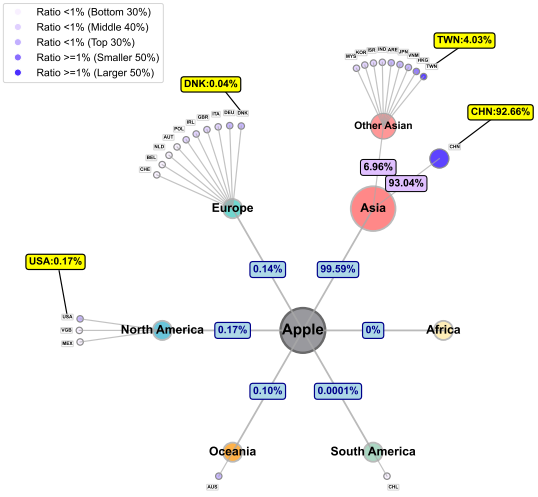
Bloomberg SPLC (2024–25)

Apple's Import Network and Top 20 Suppliers



Apple's Import Network and Top 20 Suppliers

The Average CC of Apple is 0.82



S&P Panjiva (2011-2025)

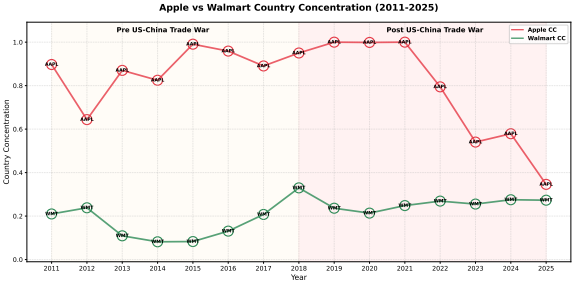
Apple: Top Suppliers by Ranking

Rank	Supplier	Country	%Cost
1	**Hon Hai**	**China**	**31.75%**
2	**Luxshare**	**China**	**12.19%**
3	TSMC	Taiwan, China	7.70%
4	**Quanta**	**China**	**7.42%**
5	LG Innotek	South Korea	5.72%
6	Samsung	South Korea	6.13%
7	QCOM	US	4.38%
8	LG Display	South Korea	4.00%
9	**Pegatron**	**China**	**3.45%**
10	SK hynix	South Korea	1.88%
11	**Lens**	**China**	**2.41%**
12	ASE	Taiwan, China	2.58%
13	**GoerTek**	**China**	**2.40%**
14	Wistron	Taiwan, China	1.59%
15	**BOE**	**China**	**2.08%**
16	**Zhen Ding**	**China**	**1.86%**
17	AVGO	US	1.72%
18	**Dongshan**	**China**	**1.35%**
19	SWKS	US	1.24%
20	MU	US	0.79%
China Total			**64.91%**

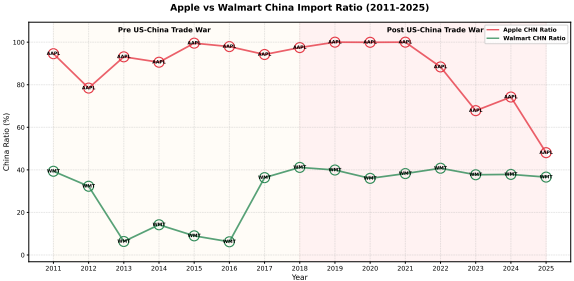
Bloomberg SPLC (2024–25)

Time-Series of CC and China Import Ratio: Apple vs Walmart

Country Concentration (CC)



China Import Ratio (%)



Apple Amidst "Liberation Day"

Apple airlifts 600 tons of iPhones from India 'to beat' Trump tariffs, sources say

By **Aditya Kalra**, **Abhijith Ganapavaram** and **Munsif Vengattil**

April 10, 2025 5:58 PM GMT+8 · Updated April 10, 2025



NEW DELHI, April 10 (Reuters) - Tech giant Apple chartered cargo flights to ferry 600 tons of iPhones, or as many as 1.5 million, to the United States from India, after it stepped up production there in an effort to beat President Donald Trump's tariffs, sources told Reuters.

About six cargo jets with a capacity of 100 tons each have flown out since March, one of them this week just as new tariffs kicked in, the source and an Indian government official said.

Apple sells more than 220 million iPhones a year worldwide, with Counterpoint Research estimating a fifth of total iPhone imports to the United States now come from India, and the rest from China.

Q2 2025 Conference Call (May 1)

Tim Cook:

- *For the June quarter, we do expect the majority of* ***iPhones sold in the US will have India as their country of origin****, and* ***Vietnam*** *to be the country of origin for almost all iPad, Mac, Apple Watch, and AirPods products sold in the US.*
- ***China*** *would continue to be the country of origin for the vast majority of total product sales outside the US.*
- *For the June quarter, we estimate the impact [...] to be* ***$900 million to our costs****.*

Concentrated Exposure to China



Trump-Xi Summit in May 2026

Lens Technology: Top Customers by Ranking

Rank	Customer	Country
1	**AAPL**	**US**
2	Xiaomi	China
3	**TSLA**	**US**
4	Huawei	China
5	Samsung	South Korea
6	VOW	Germany
7	**GOOGL**	**US**
8	BMW	Germany
9	MBG	Germany
10	Lenovo	China
11	BYD	China
12	**AMZN**	**US**
13	Huaqiang	China
14	Contemporary Amperex	China
15	LI	China
16	NIO	China
17	**META**	**US**
18	Sinocera	China

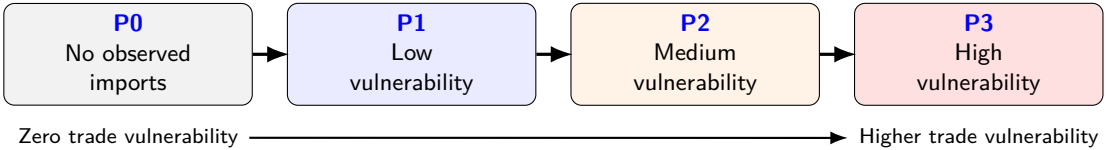
Bloomberg SPLC (2024–25)

Part II

The Market Price of Trade Vulnerability

CC-Sorted Portfolios and the Trade Risk Factor

- We sort stocks by their lagged, industry-adjusted country concentration (CC) into



- The country concentration trade risk factor:

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

- We estimate the market price of trade vulnerability via the CCTF risk premium, controlling for existing risk factors.

Summary Statistics of the CC-Sorted Portfolios

	Mean			
	P1	P2	P3	P0
Country Concentration (industry demeaned)	-0.29	-0.09	0.26	
Country Concentration	0.27	0.43	0.83	
Supplier Concentration	0.18	0.30	0.67	
HS2 Goods Concentration	0.45	0.54	0.77	
Number of Countries	15.98	10.34	4.71	
Number of Suppliers	72.60	46.76	16.03	
Number of HS2 Goods	15.19	11.35	5.83	
Import Value ($ million)	328	116	78	
Import/Revenue Ratio (%)	2.06	2.76	3.61	
China Value ($ million)	21	23	12	
China Ratio (%)	19.36	26.13	29.14	
Number of Firms	281	318	423	1726
Market Cap ($ million)	26,268	16,198	13,027	5,354
Revenue ($ million)	15,114	7,904	5,364	2,838

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 (%)	0.94	0.80	1.10	1.71	0.77	0.91
	[3.19]	[3.41]	[3.58]	[5.61]	[3.36]	[3.64]
FF5 alpha (%)	-0.09	-0.20	-0.04	0.49	0.58	0.68
	[-0.94]	[-2.62]	[-0.32]	[4.18]	[3.11]	[4.11]
MKT beta	0.99	0.89	1.00	1.08	0.09	0.19
	[76.02]	[30.27]	[27.97]	[27.10]	[2.02]	[3.05]
SMB beta	0.13	-0.03	-0.03	-0.07	-0.19	-0.03
	[3.20]	[-1.11]	[-0.53]	[-1.01]	[-2.26]	[-0.37]
HML beta	0.14	0.21	-0.03	-0.32	-0.46	-0.53
	[3.75]	[3.22]	[-0.44]	[-3.47]	[-4.10]	[-3.45]
RMW beta	-0.19	0.15	0.01	0.15	0.34	0.01
	[-2.76]	[3.49]	[0.17]	[2.39]	[3.11]	[0.06]
CMA beta	-0.08	0.16	-0.25	0.17	0.25	0.01
	[-1.04]	[1.68]	[-1.67]	[1.27]	[1.41]	[0.03]

Cumulative Returns of the Trade Risk Factor



Estimating Trade Risk Premium using Trade-Beta Sorted Portfolios

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

	Pre-Ranking Trade-Beta Sorted Portfolios					Long/Short
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Post-Ranking Beta						
MKT Beta	1.31	1.12	1.00	0.89	0.95	-0.36
	[22.66]	[35.04]	[41.60]	[39.15]	[43.77]	[-5.19]
Trade Beta	-0.43	-0.39	-0.17	-0.12	0.34	0.76
	[-5.83]	[-6.91]	[-3.66]	[-2.46]	[8.23]	[8.81]
Mean Excess Return (%)						
Ex Ret	0.67	0.84	0.94	0.86	1.37	0.70
	[1.38]	[2.14]	[2.81]	[3.39]	[4.08]	[2.21]
CAPM Alpha	-0.65	-0.29	-0.07	-0.04	0.39	1.04
	[-3.13]	[-2.22]	[-0.65]	[-0.38]	[2.85]	[3.50]
Two-Factor (MKT+Trade) Alpha	-0.25	0.07	0.09	0.07	0.08	0.33
	[-1.02]	[0.56]	[0.88]	[0.71]	[0.86]	[1.08]

Alternative Measures of Trade Vulnerability

Alternative Measures	Fama-French 5-Factor Alpha (%)					
	No Trade	Sorted Portfolios			Long/Short	
	P0	P1	P2	P3	P3 - P0	P3 - P1
Supplier Concentration (SC)	-0.09 [-0.94]	-0.12 [-2.02]	-0.05 [-0.48]	0.49 [3.19]	0.59 [2.59]	0.61 [3.34]
HS2 Goods Concentration (GC)	-0.09 [-0.94]	-0.08 [-1.65]	-0.03 [-0.22]	0.37 [3.33]	0.46 [2.59]	0.45 [3.73]
1/Number of Countries (1/NC)	-0.09 [-0.94]	-0.07 [-0.96]	0.00 [-0.02]	0.52 [2.72]	0.62 [2.42]	0.59 [2.63]
1/Number of Suppliers (1/NS)	-0.09 [-0.94]	0.02 [0.28]	-0.05 [-0.40]	0.37 [2.16]	0.47 [2.00]	0.35 [1.70]
1/Number of HS2 Goods (1/NG)	-0.09 [-0.94]	0.01 [0.17]	-0.02 [-0.15]	0.40 [2.10]	0.49 [1.87]	0.39 [1.84]
Import/Revenue (Import)	-0.09 [-0.94]	0.22 [1.82]	0.05 [0.52]	-0.14 [-1.44]	-0.04 [-0.37]	-0.36 [-2.01]
China Ratio (China)	-0.09 [-0.94]	0.13 [0.96]	-0.18 [-2.29]	0.22 [1.99]	0.31 [2.09]	0.09 [0.45]

Alternative Measures Under the Two-Factor with Trade Risk Factor

- Take the long/short portfolios constructed from the alternative measures.
- Applied to the two-factor model with trade risk factor:

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

Alternative Measures	SC	GC	1/NC	1/NS	1/NG	Import	China
Alpha (%)	0.11	0.12	0.07	0.04	0.01	-0.16	-0.07
	[0.95]	[1.02]	[0.49]	[0.25]	[0.07]	[-1.08]	[-0.92]
MKT Beta	-0.04	-0.06	0.12	0.07	0.11	-0.09	-0.01
	[-1.23]	[-1.87]	[3.02]	[1.57]	[2.24]	[-3.67]	[-0.44]
Trade Beta	0.83	0.61	0.89	0.70	0.69	0.28	0.74
	[16.47]	[7.69]	[11.87]	[9.64]	[12.57]	[4.36]	[9.78]

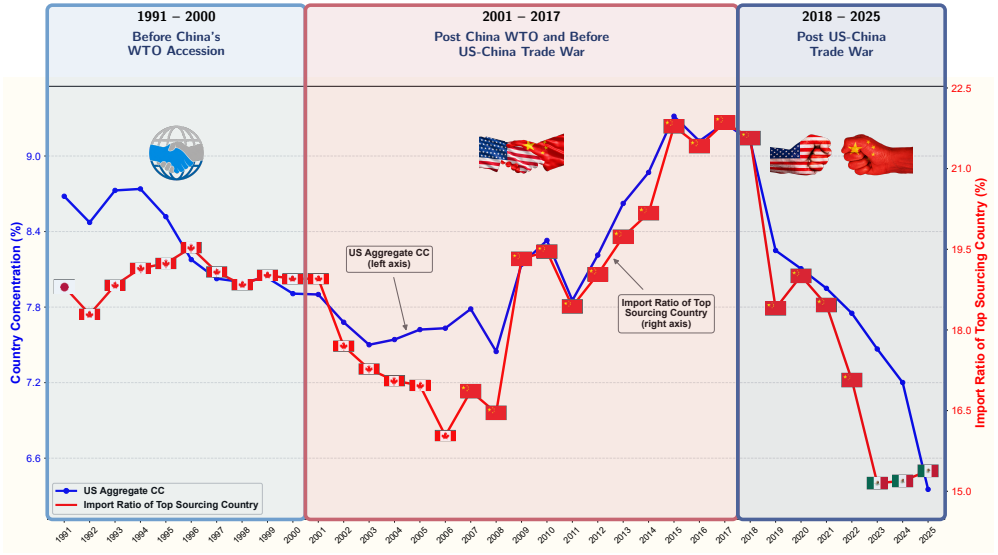
Part III

The Post-2018 Emergence of Trade Risk Premium

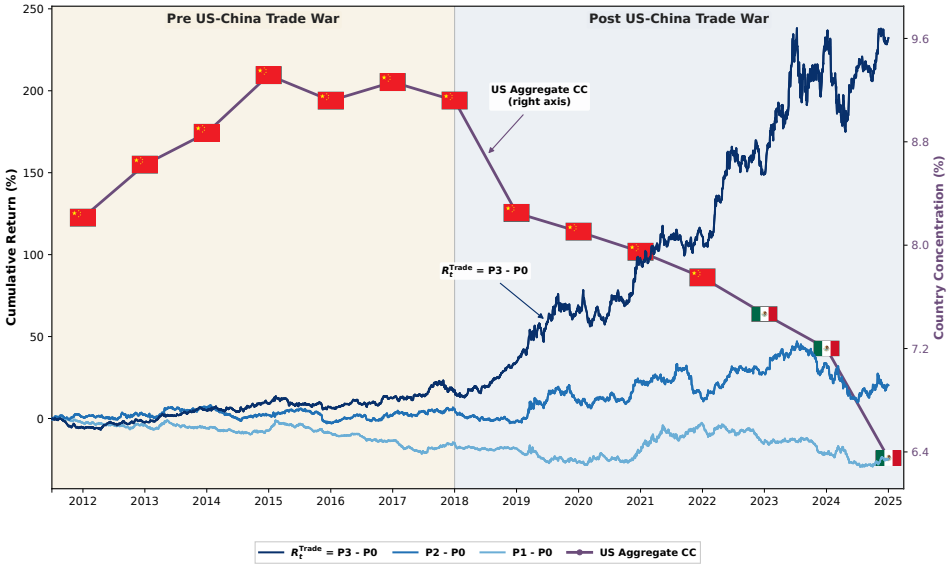
Drivers of the Trade Risk Factor and its Risk Premium

- Prior to 2018, economic efficiency drives globalization
  - U.S. firms: deeply integrated into global supply chains (e.g., Apple).
  - China: a unique supply-chain ecosystem, particularly for the tech sector.
  - *This equilibrium is difficult to dismantle – China not easily replaceable.*
- Post 2018, geopolitics fragments globalization
  - Heightened risk of sudden disruptions to global trade.
  - Trade vulnerability emerges as a systematic, undiversifiable risk.
  - Consistently, we find that
    - ⋆ Concentrated exposure to China: a key driver to the risk premium.
    - ⋆ U.S. tech firms: exhibit strong exposure to our trade risk factor and suffer from a trade vulnerability problem.

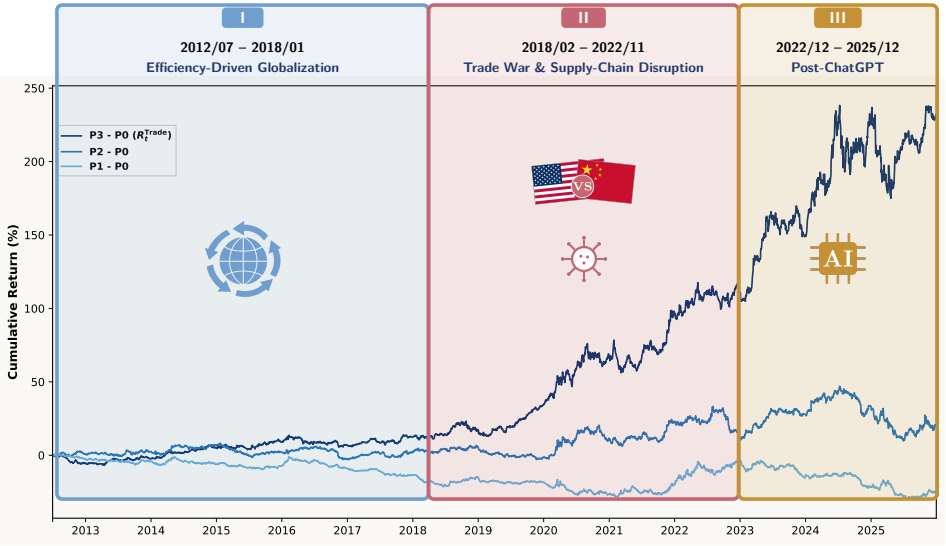
Efficiency-Driven Concentration and its Post-2018 Reversal



US Aggregate CC and Trade Vulnerability Risk Premium



The Emergence of a Trade Risk Factor



The Evolution of Trade Vulnerability as a Priced Risk

	CCTF Factor (P3-P0) Risk Premium (%)					
	I	II	III	II-I	II+III-I	III-II
Mean Ex Ret	0.18 [1.28]	1.14 [2.83]	1.27 [2.20]	0.96 [2.25]	1.01 [2.75]	0.13 [0.19]
CAPM alpha	0.31 [2.05]	1.12 [2.71]	1.11 [1.91]	0.96 [2.25]	1.02 [2.77]	0.11 [0.16]
FF5 alpha	0.20 [1.63]	0.60 [2.07]	0.99 [2.72]	0.62 [1.94]	0.81 [2.54]	0.54 [1.15]

	A Two-Factor Model with Chips Dependent Variable = CCTF Factor (P3-P0) Returns					
	I	II	III	II-I	II+III-I	III-II
alpha (%)	0.23 [1.58]	1.06 [2.73]	0.87 [1.82]	0.94 [2.26]	0.95 [2.82]	0.04 [0.06]
Market beta	-0.08 [-3.01]	0.03 [0.52]	0.02 [0.14]	0.00 [0.09]	0.02 [0.49]	0.04 [0.79]
SOX beta	0.14 [2.88]	0.09 [1.13]	0.41 [4.47]	0.11 [2.07]	0.22 [3.62]	0.24 [3.11]

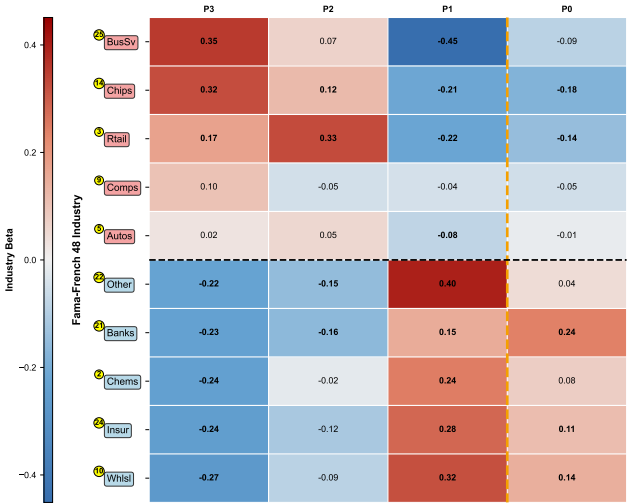
SOX: PHLX Semiconductor Sector Index

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 (%)	0.90	0.77	1.08	1.08	2.00	1.05
	[3.21]	[3.52]	[3.06]	[3.38]	[5.39]	[4.46]
alpha (%)	-0.19	-0.17	-0.11	0.00	0.67	0.11
	[-1.89]	[-1.73]	[-0.62]	[-0.02]	[4.06]	[0.75]
MKT beta	0.97	0.83	1.05	0.96	1.13	0.90
	[30.44]	[21.28]	[20.21]	[23.57]	[25.00]	[15.33]
SMB beta	0.02	-0.07	-0.07	0.04	-0.10	0.07
	[0.54]	[-1.72]	[-1.02]	[0.54]	[-0.98]	[1.19]
HML beta	0.17	0.24	-0.18	0.14	-0.37	-0.13
	[2.94]	[2.65]	[-1.87]	[2.42]	[-3.24]	[-1.33]
RMW beta	0.14	0.15	0.02	0.02	0.25	-0.07
	[1.75]	[3.47]	[0.15]	[0.19]	[2.55]	[-0.84]
CMA beta	0.10	0.21	-0.10	-0.44	-0.09	0.58
	[1.23]	[1.72]	[-0.63]	[-2.48]	[-0.54]	[3.29]

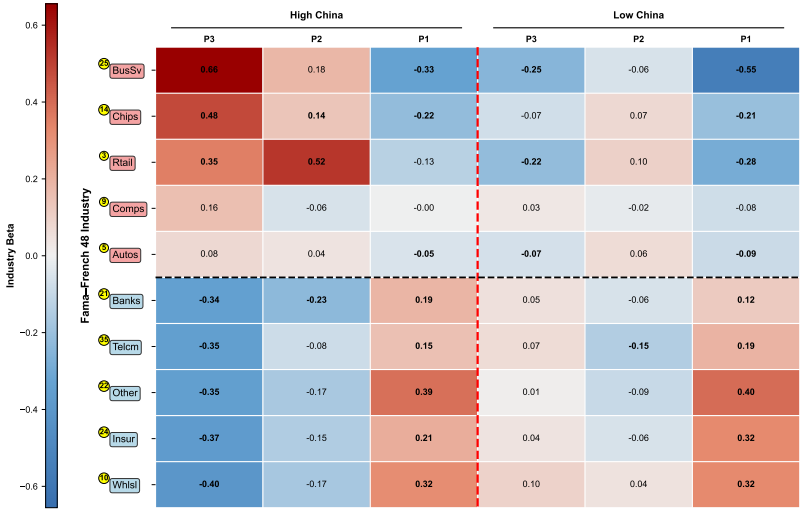
Industry Exposures of the CC-Sorted Portfolios

$$R_t^i - r_f = \alpha_i + \beta_i^{\text{MKT}} \left(R_t^{\text{MKT}} - r_f\right) + \beta_i^{\text{IND}} \left(R_t^{\text{IND}} - r_f\right) + \epsilon_t^i$$



Industry Exposures of CC×China-Sorted Portfolios

$$R_t^i - r_f = \alpha_i + \beta_i^{\text{MKT}} \left(R_t^{\text{MKT}} - r_f\right) + \beta_i^{\text{IND}} \left(R_t^{\text{IND}} - r_f\right) + \epsilon_t^i$$



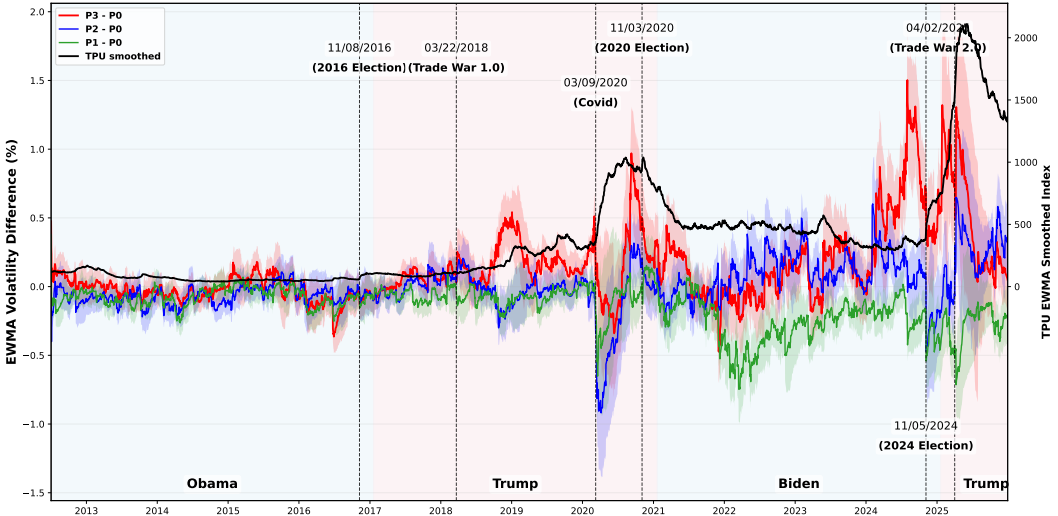
Can Tech Performance Explain the CCTF Risk Premium

	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 (%)	-0.26	-0.04	-0.05	0.25	0.52	0.29	-0.17	-0.11	-0.05	0.52	0.70	0.63
	[-2.22]	[-0.73]	[-0.60]	[3.27]	[3.13]	[2.97]	[-1.60]	[-1.72]	[-0.49]	[4.03]	[3.27]	[4.33]
MKT beta	1.06	0.91	1.03	1.01	-0.05	0.10	1.02	0.87	1.02	1.04	0.02	0.17
	[48.11]	[51.31]	[36.07]	[40.17]	[-1.59]	[2.86]	[63.84]	[38.87]	[29.05]	[30.03]	[0.42]	[3.73]
NASDAQ$^{\perp}$ beta	0.10	-0.54	-0.05	0.14	0.04	0.68	-0.28	-0.82	0.36	0.66	0.94	1.48
	[1.20]	[-7.49]	[-0.47]	[1.84]	[0.30]	[5.97]	[-3.50]	[-10.54]	[2.29]	[5.01]	[5.07]	[8.38]
alpha (%)	-0.25	0.02	-0.04	0.24	0.49	0.21	-0.11	-0.01	-0.11	0.42	0.53	0.42
	[-2.05]	[0.38]	[-0.44]	[2.95]	[2.83]	[2.22]	[-1.02]	[-0.10]	[-0.90]	[3.24]	[2.54]	[2.90]
MKT beta	1.06	0.91	1.03	1.01	-0.05	0.10	1.02	0.87	1.02	1.04	0.02	0.17
	[48.97]	[46.18]	[35.57]	[39.22]	[-1.53]	[2.62]	[65.54]	[32.09]	[29.37]	[27.58]	[0.39]	[3.15]
QQQ$^{\perp}$ beta	-0.02	-0.35	-0.06	0.09	0.11	0.44	-0.28	-0.52	0.26	0.51	0.79	1.03
	[-0.50]	[-5.51]	[-0.82]	[1.94]	[1.44]	[4.84]	[-5.16]	[-7.77]	[2.54]	[5.92]	[6.37]	[7.74]
alpha	-0.20	0.02	-0.04	0.18	0.38	0.15	-0.06	0.00	-0.12	0.33	0.39	0.33
	[-1.77]	[0.26]	[-0.38]	[2.46]	[2.47]	[1.90]	[-0.69]	[-0.03]	[-0.90]	[3.25]	[2.51]	[2.15]
MKT beta	1.06	0.91	1.03	1.01	-0.05	0.10	1.02	0.87	1.02	1.04	0.02	0.17
	[50.75]	[48.28]	[36.13]	[38.23]	[-1.51]	[2.81]	[65.65]	[30.36]	[27.12]	[28.10]	[0.39]	[3.16]
Chips$^{\perp}$ beta	-0.08	-0.14	-0.03	0.11	0.19	0.25	-0.18	-0.21	0.12	0.32	0.50	0.54
	[-2.50]	[-4.37]	[-0.74]	[5.44]	[4.77]	[6.26]	[-5.36]	[-6.02]	[2.33]	[8.39]	[8.40]	[8.50]

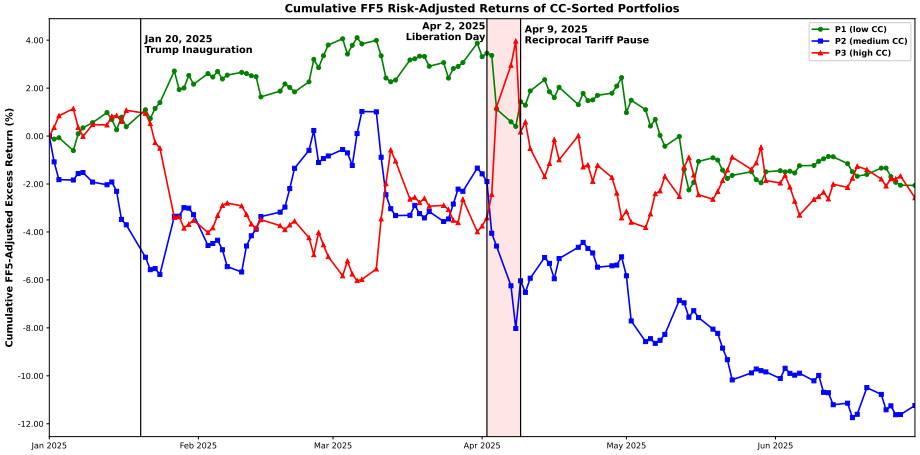
Can CCTF Explain the Tech Performance?

	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 (%)	0.06	0.29	0.36	-0.11	0.72	0.24	0.09	0.11
	[0.41]	[1.44]	[1.73]	[-0.48]	[2.56]	[1.16]	[0.39]	[0.20]
MKT beta	1.09	1.07	1.09	1.03	1.21	1.04	1.01	1.77
	[31.32]	[21.40]	[20.76]	[15.02]	[16.95]	[27.70]	[17.66]	[9.03]
	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 (%)	-0.15	-0.02	-0.10	-0.25	0.10	0.03	-0.10	-0.13
	[-1.32]	[-0.13]	[-0.67]	[-1.06]	[0.56]	[0.17]	[-0.46]	[-0.29]
MKT beta	1.09	1.06	1.08	1.03	1.19	1.04	1.00	1.76
	[36.71]	[24.32]	[25.60]	[15.59]	[19.15]	[30.68]	[18.56]	[9.15]
CCTF beta	0.29	0.41	0.61	0.18	0.83	0.28	0.24	0.32
	[7.18]	[7.14]	[11.98]	[1.81]	[11.05]	[3.84]	[3.16]	[0.96]
	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 (%)	0.05	0.21	0.11	-0.17	0.32	0.28	0.06	0.27
	[0.31]	[1.08]	[0.55]	[-0.72]	[1.29]	[1.49]	[0.26]	[0.57]
MKT beta	1.10	1.07	1.11	1.04	1.24	1.04	1.01	1.75
	[31.70]	[21.65]	[21.18]	[14.61]	[17.64]	[26.95]	[18.29]	[8.53]
CCTF beta	0.03	0.14	0.48	0.11	0.77	-0.08	0.05	-0.32
	[0.30]	[1.49]	[4.30]	[0.90]	[4.89]	[-0.67]	[0.43]	[-0.78]

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-lading data.
  - High-concentration firms, more vulnerable to disruptions in global trade, demand a significantly higher risk premium.
- Our results further show that
  - Concentrated exposure to China is a key driver of trade vulnerability and its estimated risk premium.
  - The broad-based Liberation Day tariffs hit medium-concentration firms hardest, highlighting the evolving nature of trade vulnerability.
  - U.S. tech industry exhibits strong exposure to our trade risk factor, revealing significant trade vulnerability.