Pricing the Global Trade Vulnerability

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Abstract

We document the emergence of a priced global trade risk factor amid heightened trade uncertainty. Using granular bill-of-landing data, we measure trade vulnerability by firm-level country exposure – firms with concentrated exposure to a small number of countries are more vulnerable to disruptions in global trade. Hypothesizing that the global trade vulnerability has emerged as a systematic risk, we estimate its market price by sorting stocks into portfolios with varying degrees of country concentration. Relative to low-concentration firms with diverse country exposure, high-concentration firms are riskier and earn a significantly higher risk premium, consistent with our hypothesis of a priced global trade risk factor. 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 of high-concentration firms. 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.

Keywords: Asset Pricing; Trade Vulnerability; Supply Chain Fragility; Country Concentration; Global Value Chains

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1 Introduction

Global trade has shifted over the past two decades from a period of steady growth into an era of heightened risk 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.[1] At the aggregate level, a similar pattern emerges: following China's accession to the WTO, the U.S. import structure has tilted toward a handful of dominant suppliers, with China playing a prominent role, and the country-level import concentration index has increased in tandem (Figure 1).[2] But it was not until Trump's 2018 trade war against China that the risks inherent in international trade were laid bare. If "Trump 1.0" was targeted primarily at imported goods from China, then "Trump 2.0," delivered on "Liberation Day" in 2025, represents a broader and unprecedented shock to international trade. Beyond geopolitics, the COVID-19 pandemic and ensuing supply-chain disruptions further underscored the fragility of global production networks.

As trade uncertainty becomes a central force shaping corporate decisions and driving asset allocation, we turn to financial markets to uncover the emerging risk factor associated with global trade and, importantly, to estimate the market price of trade uncertainty. Central to our analysis is the concept of *trade vulnerability*, which we measure from the ground up using firm-level import data from S&P Panjiva. Our hypothesis is that firms with more concentrated trade exposure to a small number of countries are more vulnerable to disruptions in global trade. Aggregating from micro to macro, our key insight is that, in the post–Trump 1.0 environment, trade vulnerability is no longer a purely firm-specific concern but a system-wide source of risk. Consequently, firms with higher exposure to trade risk are expected to earn higher risk premia, giving rise to a priced risk factor associated with global trade.

Our measures of trade vulnerability and the results of the asset-pricing tests can be summarized as follows. First, we construct a novel firm-level measure of trade vulnerability based on the concentration of imported inputs across source countries. Using bill-of-lading import data from Panjiva matched to publicly listed U.S. firms, we compute a country-concentration index that summarizes how heavily each firm relies on a narrow set of foreign importing countries. We then use this micro measure to construct a trade-vulnerability factor by forming portfolios sorted on firms' import-country concentration in the global

[1] McGee (2025) documents the extensive efforts made by Apple executives in Cupertino to mitigate over-dependence on a small number of suppliers in China.

[2] Figure 1 plots the evolution of U.S. import concentration over time. The blue line reports the country-concentration index, calculated as the Herfindahl index based on the top 30 import source countries in each year. The red line shows the share of total U.S. imports accounted for by the largest single trading partner in each year.

trade network. Firms with high import concentration from a limited set of countries earn an economically large positive risk premium of about 0.87% per month relative to firms with zero exposure to trade. By contrast, when we build analogous factors based on suppliers, products, or other supply-chain metrics, some of them generate positive premia but their pricing information is largely subsumed by the country-concentration-based trade factor.

Second, we uncover that the trade-vulnerability portfolios have heterogeneous exposures across industries. Firms with high trade vulnerability are disproportionately concentrated in high-technology sectors, consistent with real-economy evidence that high-tech and semiconductor firms rely heavily on globally fragmented supply chains.[3] By further decomposing China import exposure, we show that firms combining high country concentration with intensive China sourcing are central to the premium, reinforcing the tight connection between high-tech production networks and trade vulnerability (Bethmann et al., 2022). Importantly, although this overrepresentation of high-tech firms could raise concerns that the trade-vulnerability premium is merely an industry tilt, our industry-controlled tests—using both global industry reweighting and within-industry portfolio formation—demonstrate that the premium persists within industries. Finally, we show that the trade-vulnerability factor effectively explains the performance of technology and semiconductor portfolios, indicating that a substantial portion of what is commonly interpreted as "tech" or "AI" outperformance reflects compensation for bearing global supply-chain risk.

Third, we investigate how the incidence and intensity of trade vulnerability evolve over time. By estimating time-varying volatility spreads between trade-vulnerable portfolios and the zero-trade benchmark, we find that the risk of highly vulnerable firms rises sharply around major trade and supply-chain events, including the 2018–2019 U.S.–China trade war, the COVID-19 pandemic, and the 2025 "Liberation Day" tariffs. Volatility spreads for medium-vulnerability firms, unlike those for the most trade-vulnerable firms that remain at a persistently high level, increase steadily after COVID-19, converge toward those of the most vulnerable firms, and even exceed them during the "Liberation Day" shock. This pattern indicates that trade risk broadens from a narrow set of highly exposed firms to a wider segment of the corporate sector that sits at the edge of trade vulnerability. In addition, by leveraging the global trade-policy shocks around "Liberation Day" and the subsequent "Reciprocal Day," we uncover a layered pricing response: broad tariff shocks primarily depress medium-vulnerability firms, while the subsequent China-specific tariff escalation delivers an additional blow to firms with both high country concentration and high China import exposure. This evidence shows how trade risk propagates through the cross-section as the

[3]Based on the OECD report, high-tech firms have been highly profitable over the past decade, but their business models are deeply tied to offshoring and cost-saving production overseas, which makes them especially exposed to trade risk in the complex global production network (Haramboure et al., 2023).

trade-policy regime shifts.

Related Literature – Our paper belongs to the nascent literature that studies asset pricing under trade and geopolitical uncertainty. Dyakov and Jiang (2025) identify choke-point industries in global production networks and examine their asset pricing impact. Using textual data, Baker et al. (2016) measure trade policy uncertainty and, more recently, Sheng et al. (2025) measure geopolitical risk using textual analysis. Also related are the sequence of papers by Clayton et al. (2025,a,b), who offer a framework to examine how the rise of geoeconomics reshape international trade and the global financial system. Through the channel of trade vulnerability, our paper proposes a direct measure of trade risk and documents the emergence of a priced global trade risk factor amidst heightened trade and geopolitical uncertainty.

Our paper offers a fresh and unique asset-pricing perspective to the large literature on supply-chain disruptions and their impact on firms. Our focus on trade vulnerability is related to studies in trade economics and corporate finance examining the firm-level sourcing decisions in response to trade uncertainty. In Grossman et al. (2023), firms weight lower costs of offshoring against the resilience benefits of maintaining multiple supplier relationships or onshoring. Ersahin et al. (2024) provide empirical evidence that firms respond to supply-chain risk by shifting toward proximate and domestic suppliers.[4] As a direct support to our asset-pricing implication of trade vulnerability, Ahn and Tan (2025) show that products and sectors with geographically concentrated import origins are disproportionately vulnerable to exporter-specific supply shocks and tariff hikes, whereas diversified sourcing enhances resilience. Consistent with our pricing results on concentrated exposure to China, Aral et al. (2025) find that firms with concentrated reliance on Chinese suppliers suffered persistent fundamental performance losses during the U.S.–China trade war and the COVID-19 production halt, whereas firms with more diversified networks were largely insulated.[5]

Our empirical finding of an emerging global trade risk factor adds support to the network literature on the macroeconomic implications of supply-chain disruptions. Carvalho et al. (2021) and Acemoglu and Tahbaz-Salehi (2025) show that firm-level shocks propagate through input–output linkages and endogenous network formation can make aggregate out-

[4]Also related are Liu et al. (2025) on the importance of accumulating supplier capital to withstand supply disruptions, Alfaro et al. (2025) on the role of banks in mitigating trade search costs amidst disruptions, and Kim and Shin (2023) on the role of financing of working capital as a determinant of supply chain length. Alternative ways to mitigate supply chain disruptions include political connections (Cen et al., 2024) and mergers and acquisitions (Cen et al. (2025)).

[5]Despite some reallocation away from China, Alfaro and Chor (2023) show that China remains deeply embedded upstream through links with Vietnam and Mexico, implying persistent indirect exposure. Consistent with our results, China dependence alone is not priced; it amplifies trade risk only when combined with highly concentrated sourcing.

put highly fragile to local disruptions. Our paper approaches the same issue from an asset pricing perspective and provides evidence that macro-level policy uncertainty can turn firm-level trade vulnerability into a priced systematic risk. Focusing disruptions in the production of intermediate goods, Elliott and Jackson (2024) hypothesize that increased complexity of supply chains leads to increased fragility. Our pricing result by industry can potentially offer empirical evidence along this direction.

Our paper is organized as follows. Section 2 describes the bill-of-lading data and the construction of our firm-level trade-vulnerability measures. Section 3 presents the asset-pricing framework and introduces the trade-vulnerability factor. Section 4 reports the main empirical results on the pricing of trade vulnerability. Section 5 explores the economic drivers of the factor, including industry composition, China dependence, and the interplay between trade and technology exposures, and then examines the effect of imposing industry-control. Section 6 presents a series of robustness tests. Section 7 concludes.

2 Data

2.1 Data Summary

We obtain shipment-level import data from S&P Global Panjiva, a comprehensive database compiled from U.S. Customs and shipping-company bills of lading. Each observation corresponds to a distinct import transaction into the United States, providing detailed information on the U.S. consignee (importing firm), foreign shipper, country of origin, shipment date, product description (HS code), container counts, and declared shipment value. This granular data allows us to map firms' sourcing networks at the shipment-by-supplier-by-country level. Our analysis focuses on U.S. import transactions spanning 2012–2023, which represent the most complete and systematically reported segment of the Panjiva dataset, covering both public and private firms.

To ensure data quality and avoid transshipment (which should not be counted as U.S. imports), we exclude shipments with missing values for import value, weight, shipment origin, destination region, or HS codes. Additionally, we address the issue of multiple HS codes within a single shipment. Specifically, we extract the first two digits of the HS code (HS2) and calculate the percentage of each transaction that consists of identical HS2 goods. To ensure that shipment value accurately reflects the goods imported for firms' production and major supplies, we restrict our sample to transactions where 100% of the goods in the shipment share the same HS2 code.

As a result, our final dataset, which includes both private and public firms, contains 102,569,504 observations from 2012 to 2023.

The upper panel in Figure 2 compares total U.S. import values from Panjiva and the Bureau of Economic Analysis (BEA) over the period 2012–2023. On average, Panjiva captures approximately 40–46% of the total U.S. import value reported by BEA. Despite this, the dynamics of the two datasets are highly correlated, with near-perfect co-movement over time. The lower panel zooms in on imports from China, the U.S.'s largest trade partner. We compare Panjiva's marine shipment data with import data from UN Comtrade. Over the sample period, Panjiva's data on Chinese imports accounts for approximately 22–45% of the total U.S. imports from China. More importantly, the dynamics in Panjiva's data closely mirror the overall trends in U.S. imports from China, including a consistent increase from 2012 to 2015 and notable declines in 2016, 2018, and 2022, followed by recoveries in subsequent years.

In summary, the Panjiva dataset in our sample provides a highly representative picture of U.S. import behavior and dynamics, accurately capturing the trends in overall U.S. trade flows and trade with key partners like China.

2.2 Public Firm Import Data

We leverage the granularity of the S&P Global Panjiva bill-of-lading dataset to construct a comprehensive import dataset for U.S. public firms. We merge the consignee identifiers in Panjiva with Compustat using the S&P Global Company ID, which uniquely links firms across both databases. To ensure supplier information is clearly identifiable, we exclude observations with missing shipper IDs. We further standardize all shipment origins by manually mapping them to the ISO country and area codes defined by the United Nations, dropping records that cannot be matched to any recognized country or administrative area. The resulting dataset of bill-of-lading imports for U.S. public firms over 2012–2023 contains approximately 2.66 million shipment-level observations. We aggregate these shipments to the firm-year level to construct annual import measures and merge them with Compustat financial data based on firms' fiscal years.[6]

Table 1 reports the summary statistics of firm-level import measures. In the top panel, the average annual import value per firm is about $44 million, with considerable right-skewness: firms in the 99th percentile import roughly 16 times the sample average. The average firm-level import-to-revenue ratio is 2.25%, whereas the median is only 0.11%, indicating wide heterogeneity in the importance of imported goods for revenue generation.

The middle panel presents the number of import source countries, suppliers, and HS2 goods categories per firm. On average, firms import from about 5–6 countries, engage with

[6]The final sample includes 1,840 unique firms with a cumulative import value of approximately $469.9 billion over the 2012–2023 period.

20 suppliers, and import roughly 6 types of goods at the HS2 classification level. Some firms display substantially more diversified sourcing networks, with the 75th percentile and above capturing firms such as large retailers (e.g., Walmart, Ralph Lauren) that import from more than 35 countries.[7]

The lower panel of Table 1 reports the conditional import shares by continent.[8] Among firms that import from Asia, approximately 75% of their total imports originate there, underscoring the region's dominant role in global supply chains. Focusing on China, firms with Chinese imports source about 42% of their total imports from China, a share comparable to imports from Europe (44%), North America (23%), and South America (17%). Imports from Africa and Oceania are relatively minor, representing 12–14% of total imports among firms active in those regions.

Overall, these firm-level patterns mirror the aggregate structure of U.S. trade, highlighting Asia—particularly China—as the primary sourcing region for U.S. public firms during our sample period.

3 Asset Pricing Under Trade Uncertainty

3.1 Measures of Trade Vulnerability

In this study, we propose a firm-level measure of trade vulnerability, capturing the exposure of firms to trade uncertainty in global trade networks. We build this measure using firm-level data from S&P Global Panjiva, focusing on the concentration of a firm's import sources. Our primary measure is based on the Herfindahl index of country concentration (CC), which quantifies the extent to which a firm depends on a narrow set of countries for its imports.

Trade vulnerability stems from a firm's reliance on specific countries for its critical inputs, where the risk of trade reliance increases with concentration in fewer suppliers or sourcing regions when the global trade uncertainty evolves. Firms embedded in trade networks with high country concentration (i.e., importing a significant share of goods from a limited number of countries) are more exposed to shocks that disrupt those links, such as changes in trade policy, tariffs, or geopolitical tensions. This exposure can translate into increased risk, manifesting as higher expected returns, reflecting a risk premium for bearing this trade-related uncertainty.

[7]Retail and consumer firms, by nature of their global supply chains, typically have a broader sourcing footprint than manufacturing or service-sector firms.

[8]For each region, statistics are computed only for firms with nonzero imports from that region.

Country Concentration (CC): For firm i in a shipment year t, let $I_{i,c,t}$ denote the import value from country c, and let

$$I_{i,t} = \sum_c I_{i,c,t}$$

be the total import value across all countries. Define the country import share as

$$s_{i,c,t} = \frac{I_{i,c,t}}{I_{i,t}}.$$

Then the *firm-level country import concentration* is given by

$$CC_{i,t} = \sum_c (s_{i,c,t})^2 = \sum_c \left(\frac{I_{i,c,t}}{I_{i,t}} \right)^2. \tag{1}$$

Properties:

- $CC_{i,t} \in \left[\frac{1}{N}, 1\right]$, where N is the number of countries from which the firm imports in period t.
- $CC_{i,t} = 1$ if the firm imports exclusively from one country (maximum concentration).
- $CC_{i,t} = 1/N$ if the firm's imports are evenly distributed across N countries (perfect diversification).

The economic rationale for using country concentration as a measure of trade vulnerability is grounded in portfolio theory and network fragility. A diversified portfolio, in the context of a firm's trade network, offers a buffer against the negative effects of shocks originating in any single country. By sourcing inputs from a variety of countries, a firm can reduce its exposure to the risks that might affect any one trade partner. In the event of a shock—whether from geopolitical tensions, economic crises, or policy changes—a diversified firm is better positioned to absorb the impact because it can shift its sourcing to alternative suppliers or regions. This reduces the overall vulnerability of the firm's operations to any single event.

As global trade becomes increasingly interconnected, firms with concentrated import sources face higher potential costs from trade-related risks such as trade wars, tariffs, or natural disasters. In contrast, firms with diverse sourcing networks are less sensitive to such shocks because they can leverage their broader supplier base to maintain stability. For example, a firm that imports from a range of regions—such as Europe, Asia, and North America—may experience less disruption in the event of a trade shock in one region compared to a firm that sources predominantly from a single country or region.

Moreover, the concentration of imports from a few countries increases systematic risk for the firm. This is particularly relevant in the context of rising geopolitical tensions or global crises like the U.S.–China trade war and the COVID-19 pandemic, which have demonstrated the outsized impact of shocks to global supply chains. Firms with high CC values are exposed to more acute risks from these events and thus should earn a higher risk premium as compensation for bearing these risks. In contrast, diversified firms benefit from risk-sharing across a broader network of suppliers, which reduces their exposure to trade-related shocks and lowers their need for risk compensation. Therefore, the trade vulnerability captured by country concentration directly ties to the firm's exposure to systematic trade risks. Firms that rely on a narrow set of countries for their imports face greater fluctuations in supply chain reliability and should earn a higher risk premium, while firms that source from a diverse array of countries experience lower systematic risk and should, in principle, face lower risk premiums.

To illustrate the variation in trade network structures and the degree of trade vulnerability across firms, We present three representative examples from our sample—Walmart, Tesla, and Apple—each displaying distinct levels of import concentration. Figure 3(a) shows Walmart, one of the most diversified importers in our sample. Walmart sources from nearly 90 countries, with Asia accounting for roughly 90% of its total imports. Although China represents about 42%, the company also imports substantially from other Asian economies such as HongKong, India, and Vietnam, which collectively account for the remaining 58% of its Asian imports. Walmart's average Country Concentration (CC) of 0.22 indicates a well-diversified import structure, consistent with a global supply chain designed to mitigate regional trade risk.

Figure 3(b) depicts Tesla, an intermediate case with an average CC of 0.39. Tesla imports from 51 countries, with Asia and Europe representing its two major sourcing regions—about 68% and 32%, respectively. Unlike Walmart, Tesla's Asian imports are concentrated in a smaller number of countries, primarily Japan and a few others, with 82% of its Asian imports coming from just 16 countries (versus 27 for Walmart). This moderate level of diversification suggests that while Tesla spans multiple regions, its sourcing remains relatively concentrated within specific supplier hubs.

Figure 3(c) highlights Apple, a striking example of a highly concentrated importer. Apple's import network is notably sparse compared with those of Walmart or Tesla. Asia accounts for virtually all of Apple's imports, with China alone contributing about 94% of total import value. Imports from other Asian economies or continents are economically negligible. Apple's average CC of 0.88—roughly four times higher than Walmart's and twice that of Tesla's—illustrates extreme dependence on a single country, placing it among the most trade-exposed firms in our sample.

Together, these examples vividly illustrate the continuum of trade exposure captured by our country concentration measure. Walmart's globally diversified network reflects low vulnerability to country-specific trade shocks, Tesla represents an intermediate case with balanced yet regionally concentrated exposure, and Apple demonstrates extreme concentration and high systematic trade risk. These cases help clarify how country concentration (CC) provides a theoretically consistent and empirically observable proxy for firm-level exposure to global trade risk.

3.2 Portfolios of Varying Trade Vulnerability

Central to our identification of trade vulnerability is the country concentration (CC) of a firm's import exposure. We construct the portfolio based on each firm's CC in each shipment year. To account for industry variation in import intensity, we demean the firm-level CC by its industry-year average. Specifically, the demeaned CC is calculated as follows:

$$\mathrm{CC}_{i,t}^{\mathrm{demean}} = \mathrm{CC}_{i,t} - \overline{\mathrm{CC}}_{I(i),t}\,, \tag{2}$$

where $I(i)$ is firm-i's Fama–French 48 industry and $\overline{\mathrm{CC}}_{I,t}$ is the average CC of industry I in year t.[9]

Portfolio formation begins in December 2013 using stock data from the CRSP Legacy Format database (share codes 10 or 11 and exchange codes 1, 2, or 3) through 2024. Beginning in January 2025, we use the new Stock and Indexes Flat File Format 2.0 (CIZ), retaining only U.S. common stocks.

To ensure that firms' full-year trade data are available at the time of portfolio formation, we follow the UN Comtrade data release policy, which publishes country-level import and export statistics for the previous calendar year with an average reporting lag of approximately $t + 3$ months after the reference period, subject to subsequent revisions depending on each reporting country. Specifically, because full-year trade data for year $t - 1$ become available between May and June, portfolios formed before June use trade data from year $t - 2$, while those formed in June or later use data from year $t - 1$.[10]

At the end of each month t, we sort stocks into portfolios based on their industry-demeaned CC, using NYSE breakpoints to define tercile cutoffs, and compute value-weighted

[9] We thank Kenneth R. French for making the Fama–French factor returns and industry classification data publicly available through the Kenneth R. French Data Library.

[10] Although, Panjiva updates shipment records monthly with a 2–3 month lag, obtaining complete firm-level annual trade data requires waiting at least three months after the calendar year ends. To mitigate any look-ahead bias, we adopt the more conservative UN Comtrade release schedule, ensuring that portfolio formation uses only information that would have been publicly available at the time.

returns over month $t + 1$.[11] To ensure that imports are economically meaningful for firm operations, we exclude firms whose total import value is negligible relative to revenue.[12] To reduce the influence of illiquid stocks, we exclude firms with end-of-month prices below \$5, and we correct for delisting bias in returns following Shumway (1997).[13]

Finally, we sort stocks are sorted into tercile portfolios of high (P3), medium (P2), and low (P1) country concentration. Additionally, we form a benchmark portfolio (P0) consisting of firms with no import data in Panjiva for a given shipment year. Intuitively, stocks in P3 represent the most trade-vulnerable firms, as disruptions in a few key countries (e.g., China) can materially affect their supply chains. In contrast, P1 firms are more resilient, reflecting diversified sourcing across countries. Firms in P0 are primarily domestically oriented, exhibiting minimal trade exposure and serving as a benchmark group with the lowest vulnerability to international trade disruptions.

3.3 The Trade Risk Factor

Using portfolios of varying trade vulnerability as the building blocks, we construct our trade-risk factor as follows,

$$R_t^{\text{Trade}} = R_t^{P3} - R_t^{P0} . \tag{3}$$

The nature of trade vulnerability can change over time and our risk factor can also be modified accordingly. One can think of P3 as the most vulnerable, and P2 as the next in line. As such, we can also form a long/short portfolio of P2 minus P0. Similarly, while both P0 and P1 are of low trade exposure, they might also capture difference aspect of low exposure – one with zero trade while the other with very high diversification. As such, we can also test our trade-risk factor using P3 minus P1. The importance of the risk factor hinges on it risk premium and its explanatory power, an empirical endevor to be performed later in the paper.

A new risk factor emerges when it becomes a priced factor. Within our context, it is when the expected return of the factor mimicking portfolio (i.e., R_t^{Trade}) is positive and significant. The economic rationale for the positive market price of risk is that when R_t^{Trade} suffers from severe drawdowns (i.e., stocks with high concentration underforms low concentration),

[11] At each monthly formation, we use the most recently available Compustat SIC codes from fiscal year $t - 1$. Missing Compustat SIC data are filled with CRSP SIC codes available at the end of the month.

[12] We merge firms' shipping data with Compustat fiscal-year revenue to compute the import-to-revenue ratio. Firms with ratios below 0.45 basis points—indicating opportunistic or non-material import activity—are excluded. The results are robust to varying this cutoff.

[13] We restrict the sample to stocks that are tradable at month end, ensuring that portfolio formation relies on prices at which investors could plausibly transact, thereby strengthening the implementability of the measured risk premia.

the well functioning of the global trade is under attack, either because of unprecendented trade policies (e.g., 2018 US-China trade war) or supply-chain disruptions, which in turn has direct implications for macro fundamentals. As such, R_t^{Trade} is a risky portfolio of systematic importance and should carry a positive risk premium.[14]

Relative a standard asset-pricing model such as the CAPM, the emergence of a global trade-risk factor affects the pricing of stock i via

$$R_t^i - r_f = \alpha_i + \beta_i^M \left(R_t^{\text{Mkt}} - r_f\right) + \beta_i^{\text{T}} R^{\text{Trade}} + \epsilon_t^i \tag{4}$$

where R_t^i is the month-t return of firm i, R_t^{Mkt} the market return, and r_f the riskfree return. Most importantly, the pricing relation is such that, for all firm i, the idiosyncratic risk is not priced: $\alpha_i = 0$ and $E(\epsilon_t^i) = 0$.

4 Empirical Results: Pricing the Trade Vulnerability

4.1 The Empirical Performance of the CC-Sorted Portfolios

As detailed in Section 3.1, we measure trade vulnerability via the firm-level country concentration (CC) and sort stocks dynamically into portfolios of varying trade vulnerability. Table 2 summarizes the key characteristics of the CC-sorted portfolios. In addition to calculating country concentration (CC), we apply the same methodology to calculate supplier concentration and HS2 goods concentration for each firm. The first panel displays the time-series average of the cross-sectional mean and median for each concentration measure. As expected, both the industry-demeaned CC and the original CC are monotonically increasing from P1 to P3, indicating a higher level of trade vulnerability in the higher concentration portfolios. Interestingly, the supplier and goods concentration measures show a similar pattern of monotonic increase from P1 to P3, suggesting that these measures may capture overlapping information about trade vulnerability.

The second panel presents the portfolio averages for the number of countries, suppliers, and HS2 goods each firm imports from. These results align with the economic implications of the CC. For example, the stocks with the highest trade vulnerability (P3) import from fewer countries, averaging about 3 countries, compared to 7 countries for firms in P2 and 12 countries for firms in P1 (low trade vulnerability). Similarly, the number of suppliers and types of goods follows a similar pattern. High trade vulnerability firms not only import from fewer countries but also have fewer suppliers and a limited variety of goods, importing on

[14] As in any standard asset-pricing model, the risk captured by R_t^{Trade} will enter into the pricing kernel and carry a positive market price of risk.

average just 3-4 different types of goods. In contrast, firms with lower trade vulnerability (P1) diversify their supply chains by sourcing from more suppliers and importing a broader range of goods.

The third panel calculates the average total import value and its ratio scaled by the total revenue for each portfolio. The average total import value shows a clear monotonic decreasing pattern. Firms with more diversified trade networks in P1 import about three times more than firms with more concentrated networks in P3. However, the median value is much smaller than the cross-sectional mean of total import value, indicating that each portfolio contains firms with a few outliers importing very large amounts. The import/revenue ratio does not exhibit a perfectly monotonic relationship with trade vulnerability when considering the cross-sectional mean. However, the median import/revenue ratio reveals a clear pattern: it decreases from 0.34% in P1 to 0.11% in P3. This suggests that for low trade vulnerability firms (P1), the import share of their revenue is relatively more compared to high vulnerability firms, where imports constitute a small proportion of their revenue.

The bottom panel reports summary statistics on the number of firms, market capitalization, revenue, return on assets (ROA), and operating margin across trade-vulnerability portfolios. The benchmark portfolio (P0) includes approximately 2,190 firms with no import activity in a given shipment year, indicating that the majority of U.S. firms have no direct trade exposure. Among importing firms, the number of observations increases with trade vulnerability, with 229 firms in the highest-vulnerability portfolio (P3), compared to 175 in P1 and 195 in P2.

Market capitalization and revenue display a non-monotonic pattern. While firms in P3 are substantially larger than firms in P0—averaging \$18.3 billion in market capitalization and \$6.7 billion in revenue versus \$6.5 billion and \$3.9 billion in P0—firms in P1 are the largest among importing firms, with size declining monotonically from P1 to P3. This pattern indicates that extreme trade vulnerability is not driven by firm size alone.

Profitability measures reveal substantial dispersion. Return on assets (ROA) is negative on average for the zero-trade benchmark (P0) but remains positive on average for all trade-exposed portfolios; among importing firms (P1–P3), ROA declines monotonically with trade vulnerability, with P1 firms the most profitable and P3 firms the least profitable. In contrast, operating margins exhibit pronounced left-tail losses, with negative means but positive medians in both P0 and P3. Importantly, among trade-exposed firms, average operating profitability deteriorates sharply with trade vulnerability. Taken together, these patterns suggest that the higher expected returns earned by highly trade-vulnerable firms are unlikely to be driven by superior operating performance. Instead, they are consistent with a risk-based interpretation in which firms with concentrated sourcing structures face greater downside exposure to supply-chain disruptions and therefore command higher risk premia.

4.2 The Emergence of a Priced Trade Risk Factor

As detailed in Section 3.3, we construct the trade risk factor using the CC-sorted portfolios. Table 3 reports the main asset-pricing results. Our primary variable of interest is the trade-vulnerability factor (HL30), defined as the return differential between the portfolio of highly trade-vulnerable firms (P3) and the benchmark portfolio of firms with zero trade exposure (P0). We also construct an alternative factor, HL31, defined as the return spread between P3 and the low-vulnerability portfolio (P1). HL31 thus captures return differences among firms with trade exposure but varying degrees of concentration.

Panel A presents the Pearson correlations between the two trade factors (HL30 and HL31) and the five Fama–French factors of Fama and French (2015). The two trade factors are highly correlated (0.84), indicating that they capture closely related dimensions of trade-risk exposure. Nevertheless, HL30 is the more representative measure because its benchmark portfolio (P0) consists of firms with no international trade exposure. Both trade factors exhibit low correlations with the market factor—0.14 for HL30 and 0.30 for HL31—implying that trade-vulnerability risk is largely orthogonal to aggregate market risk.

With respect to the other Fama–French factors, HL30 correlates negatively on size (–0.29), value (–0.42), and investment (–0.28), and positively on profitability (0.27). These patterns align with the portfolio characteristics in Table 2: relative to zero-exposure firms (P0), highly vulnerable firms (P3) are larger and more profitable, suggesting that trade concentration is not merely a proxy for small, distressed, or unprofitable firms. HL31 shows similar negative correlations with value and investment, while its correlations with size and profitability are near zero. Overall, the correlations suggest that the trade-vulnerability factors represent an economically distinct dimension of risk that is only weakly related to conventional systematic factors.

We then conduct time-series factor-pricing tests for the trade-vulnerability portfolios and the long–short portfolios HL30 and HL31. Specifically, we estimate

$$R_t^{\mathrm{T}} = \alpha_{\mathrm{T}} + \beta_{\mathrm{T}}' f_t + \varepsilon_t^{\mathrm{T}}, \tag{5}$$

where R_t^{T} denotes the excess return on portfolio $\mathrm{T} \in \{\mathrm{P0}, \mathrm{P1}, \mathrm{P2}, \mathrm{P3}, \mathrm{HL30}, \mathrm{HL31}\}$, f_t is a vector of pricing factors (either the market factor for the CAPM or the Fama–French five factors), and β_{T}' is the corresponding vector of factor loadings.

Panel B reports the time-series pricing results for the value-weighted excess returns of the trade-vulnerability portfolios. Among trade-exposed firms, average excess returns increase monotonically with trade vulnerability, from P1 to P3. Firms with zero trade exposure (P0) and trade-resilient firms (P1) earn roughly 0.8% per month, medium-vulnerability firms (P2) earn about 1.0% per month, and the most trade-vulnerable firms (P3) earn 1.71% per month—more than twice the return of the zero-trade benchmark. Consequently, the long–short HL30 factor (P3–P0) earns an economically large and statistically significant risk premium of 0.86% per month, while the HL31 factor (P3–P1) yields a slightly higher premium of 0.90% per month.

To explore the time-series dynamics of these trade factors, we construct a daily HL30 portfolio and plot its cumulative performance in Figure 4, together with the comparison spreads P2–P0 and P1–P0. The cumulative trade-factor return rises steadily from 2014 through early 2017, accelerates during the 2017–2021 period, and displays pronounced volatility in late 2018–2019—coinciding with the escalation of U.S.–China trade tensions.[15] The factor becomes more volatile again in early 2020 during the COVID-19 pandemic, reflecting widespread supply-chain disruptions. During the 2021–2024 period, HL30 continues to trend upward, with episodic volatility spikes linked to renewed policy uncertainty. A sharp decline in late 2024, coinciding with the U.S. presidential election, underscores the sensitivity of the factor to shifts in trade-policy expectations. By contrast, the P1–P0 spread remains comparatively stable over time, exhibiting limited volatility and weaker cumulative growth. The P2–P0 spread remains relatively stable before 2025 but becomes noticeably more volatile thereafter, showing a modest downward trend following the "Liberation Day" period. Overall, the time-series dynamics of HL30 indicate that trade-vulnerability risk intensifies during episodes of heightened global trade uncertainty.

We next examine the pricing evidence for each trade-vulnerability portfolio under the CAPM and the Fama–French five-factor model. The middle and lower panels of Table 3 report the results. Under the CAPM, and with the exception of the most vulnerable portfolio (P3), none of the other portfolios (P0, P1, or P2) deliver statistically significant alphas. In contrast, the P3 portfolio continues to earn a strong positive and significant risk-adjusted return of 0.65% per month ($t = 3.51$), confirming that high trade-vulnerability firms command an incremental risk premium beyond the market factor. Importantly, the trade-vulnerability factor HL30 also remains significantly priced, with a positive and significant alpha of 0.78% per month, consistent with investors demanding compensation for bearing exposure to global trade uncertainty. The HL31 factor yields a similar pattern, with a positive and significant risk premium of 0.69% per month after adjusting for the market factor.

In the lower panel, we find qualitatively similar evidence under the Fama–French five-

[15] See the timeline of the U.S.–China trade war provided by PIIE.

factor model, although the risk-adjusted returns of P3, HL30, and HL31 are somewhat reduced in magnitude. To further interpret these results, we examine the factor betas across portfolios. The benchmark portfolio (P0) of zero-exposure firms, while having a relatively high market beta, loads positively on the size and value factors and negatively on the profitability and investment factors, consistent with its composition of smaller, less-profitable, value-oriented firms. In contrast, the most trade-vulnerable portfolio (P3) exhibits an insignificant or slightly negative loading on size, a negative loading on value, and a positive significant loading on profitability—indicating that these firms are generally larger, growth-oriented, and more profitable. Consequently, the long–short HL30 factor (P3–P0) captures the return spread between portfolios with sharply different exposures to global trade risk while largely offsetting their exposures to the conventional Fama–French factors.

Overall, these findings demonstrate that firms with greater exposure to concentrated trade networks earn systematically higher expected returns, and that the resulting trade-vulnerability factor commands a positive and significant risk premium that is distinct from standard asset-pricing factors. This evidence suggests that investors require compensation for bearing risks associated with global trade uncertainty—a risk dimension that has become increasingly salient as trade dynamics have evolved over the past two decades. In particular, the transition from an era of stable globalization to one marked by recurrent trade tensions, supply-chain disruptions, and policy-induced shocks has amplified the pricing relevance of trade vulnerability. Overall, the results highlight that global trade uncertainty represents a dynamically evolving, priced source of systematic risk in financial markets.

4.3 Alternative Measures of Trade Vulnerability

Having established that the country–concentration-based trade factor (HL30) captures a priced source of global trade risk, we next examine whether alternative measures of trade vulnerability contain similar pricing information. Specifically, we follow the same logic as the country concentration (CC) measure to construct supplier concentration (SC) and goods concentration (GC) based on the first two digits of the HS codes. We also consider the inverse number of countries (1/NC), suppliers (1/NS), and goods (1/NG) from which a firm imports, as these variables are closely related to the construction of concentration measures. In addition, we evaluate the import-to-revenue ratio as a measure of import cost intensity and the China import ratio as a proxy for dependence on Chinese imports.[16]

Panel A of Table 4 reports Fama–French five-factor alphas for portfolios formed on these alternative trade-vulnerability measures. We find that portfolios sorted by supplier concentration (SC), goods concentration (GC), and the inverse number of countries (1/NC)

[16] The detailed construction of each measure is provided in Appendix 8.1.

exhibit pricing patterns that are closely aligned with those based on country concentration (CC). For these three measures, the long–short spreads between the highest-vulnerability and zero-trade portfolios (P3–P0) are positive and statistically significant, with monthly alphas of 0.44%, 0.34%, and 0.57%, respectively. These results are consistent with the evidence in Table 2, which shows that firms with high country concentration also tend to have more concentrated supplier and product networks and to source from fewer countries. Notably, the P3–P0 premium for portfolios sorted on 1/NC is of the same order of magnitude, though smaller, than the CC-based trade factor premium, reflecting the fact that the number of import countries is a direct input into the construction of CC. Overall, the similar pricing implications across these related measures reinforce the interpretation that country-level import concentration captures a robust and economically meaningful dimension of firms' exposure to trade vulnerability.

In contrast, when we condition on firms with nonzero trade exposure (P3–P1), the return spreads for these alternative measures remain positive but lose statistical significance, except for SC, where the long–short spread is only marginally significant. This further supports the view that the CC measure is the most robust and informative metric for capturing trade-related risk among firms that are already engaged in global sourcing.

Other measures perform less well. Portfolios sorted by 1/NS and 1/NG do not display consistent pricing implications, although the P3–P0 spread formed on 1/NS is marginally significant at the 10% level. Portfolios sorted by the import-to-revenue ratio exhibit a monotonic decline in risk-adjusted returns from P0 to P3, with negative long–short spreads, suggesting that import intensity alone does not proxy for trade vulnerability. Finally, while portfolios sorted by the China import ratio display a monotonic increase in returns from P0 to P3, the corresponding P3–P0 spreads are not statistically significant.

Given that several alternative measures—particularly SC, GC, and 1/NC—carry pricing information consistent with exposure to global trade uncertainty, we next assess whether these return premia are fully explained by our trade factor. To this end, Panel B of Table 4 contrasts the CAPM with a two-factor model (Equation (4)) that augments the market factor with the CC-based trade factor (R^{Trade}). Under the CAPM, the long–short portfolios (P3–P0) based on SC, GC, 1/NC, and even 1/NS and the China import ratio yield positive and statistically significant alphas. However, once we include R^{Trade} alongside the market factor, the risk-adjusted returns of these alternative long–short portfolios become statistically indistinguishable from zero. The CC-based trade factor effectively absorbs the positive premia previously attributed to SC, GC, 1/NC, and the China import ratio driving their alphas to negligible levels. Although the long–short portfolios based on 1/NS and 1/NG do not exhibit robust premia to begin with, their modest positive alphas are further attenuated under the two-factor specification.

All seven long–short portfolios load positively and significantly on the CC-based trade factor, albeit with differing magnitudes. Among them, the 1/NC portfolio exhibits the largest loading (approximately 0.94), consistent with its close theoretical and empirical link to CC. The trade-factor betas for the SC, GC, 1/NS, 1/NG, and China import ratio portfolios lie between 0.36 and 0.78, confirming meaningful exposure to the underlying trade-vulnerability channel. By contrast, the import-to-revenue portfolio displays only a modest and marginally significant loading on R^{Trade}, reinforcing the notion that import intensity by itself is not a key driver of the priced trade risk.

Taken together, these results show that although a number of alternative trade measures exhibit some pricing power, their explanatory content is largely subsumed by the CC-based trade factor. The evidence highlights that country concentration captures the dominant channel through which global trade uncertainty is priced in equity markets, confirming its central role as the most informative and robust measure of firms' exposure to evolving trade-related risks.

5 Understanding the Drivers of the Trade Risk Factors

5.1 Concentrated Exposure on China as a Key Driver

In this section, we investigate whether the trade-vulnerability risk premium is primarily driven by firms' dependence on a single dominant import partner, namely China. A large literature documents China's rise as a central node in global supply chains and the magnitude and persistence of the resulting "China shock" for the U.S. economy.[17] Based on UN Comtrade, U.S. imports from China have risen sharply following China's WTO accession in the early 2000s. As shown in Figure 1, China overtakes Canada to become the United States' largest import source and reaches a historical peak of about 22% of total U.S. imports in 2017, consistent with the aggregate patterns in Alfaro and Chor (2023). Over the same period, the U.S. country-level import concentration, measured by the Herfindahl index, comoves closely with the China import share (Figure 1). The U.S. import CC trends upward from around 2007, peaks between 2015 and 2017, and begins to decline after 2018, coinciding with the onset of the U.S.–China trade war. Motivated by this macro pattern and the central role of China in U.S. supply chains, we ask whether firms' China import exposure is an important driver of the trade-vulnerability risk premium, conditional on their overall

[17] See, among others, Alfaro and Chor (2023) on the "great reallocation" of U.S. sourcing away from China after 2017, Autor et al. (2021) and Caliendo et al. (2019) on the employment and welfare effects of Chinese import competition, and Handley and Limão (2017) on the role of U.S.–China trade policy uncertainty around WTO accession.

country concentration.

We examine this channel using a conditional bivariate sorting strategy. Within each country-concentration (CC) portfolio, we sort firms on their China import ratio, defined as the firm's total import value from China divided by its total import value across all countries in a given shipment year. Because firms may not import from China every calendar year, using a single year could mechanically assign a zero China share to firms that import from China intermittently. To mitigate this issue, we use a two-year window and select the most recent available shipment records for imports from China. If a firm has imports from China in year $t-1$, we use its year $t-1$ China import ratio; otherwise, we look back to year $t-2$. If the firm imports nothing from China in both years $t-1$ and $t-2$, we classify it as having zero China imports at the portfolio-formation date.[18]

We first sort stocks into three CC portfolios (P1, P2, P3) and, within each CC portfolio, compute the cross-sectional median of the China import ratio. Firms with a China import ratio above the within-portfolio median are classified as High China, and those with a ratio at or below the median are classified as Low China. This procedure yields six portfolios: P1×High China, P1×Low China, P2×High China, P2×Low China, P3×High China, and P3×Low China. Our main objective is to assess whether the CC trade-vulnerability risk premium is concentrated among firms with high China import intensity.

The left panel of Panel A in Table 5 reports the value-weighted excess returns of these six portfolios. We observe a clear monotonic increase in returns from low to high country concentration among firms with high China import exposure, whereas no such pattern emerges among firms with low China dependence. Among High-China firms, stocks with high country concentration (P3×High China) earn an average monthly excess return of 2.03%, which is approximately 2.4 times the 0.84% per month earned by low-concentration firms with similarly high China exposure (P1×High China). Thus, conditional on high China import intensity, the P3–P1 spread is about 1.18% per month and statistically significant. By contrast, the P3–P1 spread among Low-China firms is economically small (0.13% per month) and statistically insignificant. The difference between the high–low CC spreads across High-China and Low-China groups—a "double-difference" between (P3–P1)×High China and (P3–P1)×Low China—is itself significantly positive at about 1.06% per month, indicating that the trade-vulnerability premium is much stronger among firms with high China dependence.

[18]For example, if a firm has import records from China in year $t-1$, we use its China import ratio from year $t-1$. If the firm has no China imports in year $t-1$, we look back to year $t-2$. If the firm has no imports from China in either year $t-1$ or $t-2$, we define its China import ratio as zero at the time of portfolio formation. This two-year window reduces the chance of misclassifying firms with intermittent or seasonal China imports as non-importers.

We next compare High-China and Low-China portfolios within each CC group. Only within the high-concentration portfolio (P3) do we find a statistically significant spread between High-China and Low-China firms: the High–Low China portfolio within P3 earns an average monthly excess return of approximately 1.10%. In contrast, the High–Low China differences within P1 and P2 are small and statistically insignificant. The right panel of Panel A of Table 5 reports the average industry-demeaned CC for each of the six portfolios and confirms that the CC dimension behaves as designed: P3 portfolios consistently exhibit higher CC than P1 portfolios, irrespective of China exposure.

Panel B of Table 5 reports the Fama–French five-factor regressions for the six base portfolios and the relevant High–Low and double-difference spreads. After controlling for the five factors, only firms with both high country concentration and high China import ratios (P3×High China) continue to earn a positive and statistically significant alpha of about 0.68% per month. Consistent with this, the CC spread (P3–P1) conditional on High-China exposure also remains positive and significant, with an alpha of roughly 0.81% per month. In contrast, the remaining CC×China portfolios and their associated High–Low China spreads do not retain statistically significant risk-adjusted returns. Nevertheless, the magnitudes of the P3 High–Low China spread and the corresponding double-difference portfolio remain economically large, even though factor adjustments absorb part of the statistical significance. Firms with high trade vulnerability and high China import exposure also appear to be more exposed to systematic risks: they exhibit relatively high market betas, larger firm size, growth characteristics (negative loadings on size and value), and higher profitability (positive and significant loadings on the profitability factor) compared with firms in other portfolios.

Table 6 provides further evidence by comparing firm characteristics across these portfolios. First, high-China firms in P3 have much higher China import ratios than high-China firms in P1, consistent with P3 firms being more concentrated in a small set of countries and relying more heavily on China as a key supplier. Conditional on importing from China, firms in P3 lack the diversified trade networks available to firms in P1 and thus depend more intensively on Chinese imports. Second, in terms of trade structure, high-China firms in P3 exhibit greater supplier and goods concentration than high-China firms in P1. However, within P3, high-China firms actually have lower supplier and goods concentration than low-China firms, a pattern that is echoed in the counts of countries, suppliers, and goods: high-China firms in P3 source from more countries, more suppliers, and more HS2 goods than their low-China counterparts, despite similar overall country concentration. Third, high-China firms in P3 have the highest import-to-revenue ratios of any portfolio, indicating that imports—especially those from China—are particularly important for their revenue generation. Finally, on the size dimension, high-China firms in P3 are substantially larger than high-China firms in P1, and within P3, high-China firms are roughly 2.6 times larger in market value than low-China firms.

Overall, the evidence indicates that the trade-vulnerability risk premium is especially pronounced among firms that combine high country concentration with high China import dependence. This pattern is consistent with the view that China-related trade shocks and policy uncertainty—documented to have large and persistent real effects in both reduced-form and general-equilibrium settings (e.g., Autor et al., 2021; Caliendo et al., 2019; Handley and Limão, 2017) and to be rapidly priced in equity markets for China-exposed firms (Huang et al., 2023)—are a key driver of the priced trade-related risk captured by our factor.[19]

5.2 Industry Exposures of the Trade Risk Factors

Global supply-chain disruptions in recent years have highlighted that technology-intensive industries are among the sectors most exposed to trade-related risks. Semiconductors—an essential upstream input for ICT, electronics, automotive, and advanced manufacturing—are produced through a highly fragmented and geographically concentrated value chain (Haramboure et al., 2023). The OECD's semiconductor ICIO analysis shows that semiconductor production is both one of the most upstream and one of the most concentrated industries globally, with a small set of Asian economies accounting for the majority of global value added; disruptions in any of these locations can propagate widely across downstream industries and economies. Motivated by this structural vulnerability of the technology sector, we next examine whether the trade-vulnerability portfolios load differently across industries, and in particular whether they exhibit systematically stronger connections to technology-linked industries.

5.2.1 Industry Exposures of the CC-Sorted Portfolios

We begin by estimating Fama–French 48 industry betas for the trade-vulnerability portfolios. To isolate industry-specific variation, we first remove market information from each industry portfolio by regressing its excess return on the market factor and constructing a market-orthogonalized industry factor as the sum of the CAPM alpha and the regression residual. We then estimate industry betas for each trade-vulnerability portfolio by regressing its excess return on these orthogonalized industry factors, along with the market factor.

The upper panel in Figure 5 presents a heatmap of industry betas, with bold values indicating significance at or beyond the 5% level. To highlight patterns for the most vulnerable

[19]From an asset-pricing perspective, our evidence complements event-study results such as Huang et al. (2023), who show that U.S.–China tariff announcements generate disproportionately negative stock-price reactions for firms with direct and indirect trade links to China.

firms, we compare the top ten and bottom ten industry betas for P3 with the corresponding betas of the other portfolios.[20] The three largest and most significant industry exposures for P3 are Chips (0.46), Business Services (0.24), and Retail (0.17). Other industries appearing in P3's top- or bottom-ten lists exhibit statistically insignificant exposures. Notably, P2 also loads positively and significantly on the same three industries, albeit with different magnitudes. In contrast, firms in P1—the low-vulnerability portfolio—tend to load positively on industries that appear in P3's bottom-ten group, with eight significant exposures, and display either negative or near-zero betas for the industries that comprise P3's top-ten exposures. Finally, P0 (firms with zero trade exposure) largely mirrors the exposure pattern of P1.

In sum, these results show that the firms most exposed to trade vulnerability—those in P3 who contribute the risk premium—have systematically stronger connections to technology-linked industries, particularly the semiconductor sector. This pattern aligns with the OECD's evidence that semiconductor and ICT-related industries are structurally vulnerable to global supply-chain risk and trade uncertainty (Haramboure et al., 2023).

5.2.2 Country Concentration and China Exposure

As the high trade-vulnerability portfolio exhibits its strongest exposures in technology-linked industries, the extent of these sectoral connections depends critically on firms' sourcing patterns. A growing body of evidence shows that U.S. computer and electronics industries are among the sectors most exposed to China, which has become the dominant supplier of intermediate and capital goods essential to advanced manufacturing (Caliendo and Parro, 2023). This dependence is further reinforced by the structure of ICT supply chains: major U.S. technology firms rely on multi-tier supplier networks rooted in China, with more than half of their upstream component shipments originating from Chinese production sites.[21] These patterns suggest that China-centered sourcing may amplify the technology-sector exposures observed for the most trade-vulnerable firms. We therefore examine whether the industry exposures of our trade-vulnerability portfolios differ systematically when conditioning on firms' China import dependence.

We begin by estimating Fama–French 48 industry betas for the six portfolios formed by the interaction of country concentration (P1, P2, P3) and China import exposure (High versus Low). To highlight the channels relevant for the most vulnerable firms, we compare the top and bottom ten industry betas for the P3 $\times$ High-China portfolio with the corresponding

[20] The yellow circle and accompanying number next to each industry name denote the industry's rank in total import value within our sample.

[21] See Beeny (2018), *Supply Chain Vulnerabilities from China in U.S. Federal ICT*, Exhibit 1 on page 2.

betas for the remaining portfolios. The lower panel in Figure 5 presents the heatmap of these industry exposures.

We find that high-vulnerability firms with high China import ratios load positively and significantly on several technology-linked industries, including Chips, Business Services, Retail, Computers, and Autos. The Chips, Business Services, Retail, and Autos betas are all statistically significant at or beyond the 5% level. Notably, the Chips beta for the P3 $\times$ High-China portfolio is 0.74—approximately 1.6 times larger than the corresponding Chips beta for the P3 portfolio alone—indicating that China import intensity substantially amplifies the technology-sector sensitivity of firms with concentrated sourcing networks. A similar amplification is observed for Business Services and Retail.

In contrast, high-vulnerability firms with low China import ratios exhibit almost the opposite pattern: their largest exposures lie in industries that fall within the bottom-ten group of the P3 $\times$ High-China portfolio, and they load negatively or insignificantly on the top-ten high-tech industries. Turning to P2 $\times$ China portfolios, we observe a similar, although somewhat muted, pattern of stronger technology-sector exposures for high-China firms than for low-China firms. By comparison, firms in P1—the least trade-vulnerable group—show little heterogeneity across China import exposure: both High-China and Low-China P1 portfolios load positively on the industries that correspond to the bottom-ten group of the P3 $\times$ High-China portfolio, and they load negatively or near zero on P3's top-ten industries.

Overall, by decomposing China import exposure within each trade-vulnerability group, we find consistent evidence that China-centered sourcing amplifies the technology-sector exposures of the most trade-vulnerable firms. This mirrors real-side evidence documented by Bloom et al. (2016), who show that Chinese import competition induces technological upgrading and reallocation toward high-tech, IT-intensive firms in advanced economies. Our results complement this evidence by demonstrating that firms operating at the intersection of concentrated sourcing and China-dependent supply chains also bear heightened priced exposure to the technology-sector risks embedded in global value chains.

5.3 Industry-Controlled Trade Vulnerability

5.3.1 Pricing of Industry-Controlled Trade Vulnerability Portfolios

While the strong technology tilt of the high-vulnerability portfolios is an economically meaningful feature of global production networks, an important question is whether the estimated trade-vulnerability premium simply reflects industry composition rather than exposure to concentrated sourcing itself (Haramboure et al., 2023). High-technology industries—particularly semiconductors, electronics, and ICT-related manufacturing—are structurally more exposed to globally fragmented input networks and are therefore naturally overrepresented in the high-CC portfolio. To ensure that the trade-risk premium is not mechanically driven by this sectoral concentration, we examine industry neutrality from two complementary angles. First, we impose *global industry-neutral weighting*, reweighting each CC portfolio to share a common benchmark distribution across the Fama–French 48 industries. Second, we implement *within-industry sorting*, forming CC portfolios separately inside each industry to eliminate cross-industry variation by construction. Together, these two approaches allow us to assess whether the trade-vulnerability premium persists once industry tilts are removed and to identify how the premium arises across industries.[22]

Specifically, within each CC portfolio $p \in \{\mathrm{P0}, \mathrm{P1}, \mathrm{P2}, \mathrm{P3}\}$, we first compute value-weighted returns for each industry j represented in the portfolio:

$$R_{p,j,t+1} = \sum_{i \in (p_t \cap j)} \frac{\mathrm{MktCap}_{i,t}}{\sum_{k \in (p_t \cap j)} \mathrm{MktCap}_{k,t}} \, r_{i,t+1}, \qquad \text{if } (p_t \cap j) \neq \emptyset.$$

To construct a common benchmark, we compute market-capitalization weights for the Fama–French 48 industries using the full sample at month-end t:

$$\omega_{j,t} = \frac{\sum_{i:\,\mathrm{FF48}(i)=j} \mathrm{MktCap}_{i,t}}{\sum_{k=1}^{48} \sum_{i:\,\mathrm{FF48}(i)=k} \mathrm{MktCap}_{i,t}}, \qquad \sum_{j=1}^{48} \omega_{j,t} = 1.$$

Because each CC portfolio contains only a subset of the 48 industries, we rescale the global industry weights to the industries present in portfolio p. Let n_p denote the number of industries in p. The rescaled benchmark weights are:

$$\hat{\omega}_{j,t} = \frac{\omega_{j,t}}{\sum_{j=1}^{n_p} \omega_{j,t}}.$$

We then compute the industry-neutral return for portfolio p as:

$$R^{INT}_{p,t+1} = \sum_{j=1}^{n_p} \hat{\omega}_{j,t} \, R_{p,j,t+1}.$$

This approach enforces identical industry exposures across portfolios so that return differences reflect firm-level trade vulnerability rather than industry composition, substantially

[22] Novy-Marx (2013) highlights the importance of removing industry effects in factor construction, implementing industry hedges and industry-demeaned characteristics to isolate characteristic premia. In the same spirit, we impose industry-neutral weighting so that differences in portfolio returns are not driven by industry composition. For related approaches that construct industry-neutral portfolios using within-industry sorting, see Asness et al. (2014).

reducing the influence of technology-sector tilts on the estimated trade-risk premium.

Finally, when constructing long–short trade-risk factors—such as P3–P0 or P3–P1—we impose exact industry neutrality by restricting both legs of the factor to the intersection of industries they jointly contain. This guarantees that the long and short sides share the same industries with identical benchmark weights, so the resulting high-minus-low spread represents a strictly industry-matched comparison. As a result, these industry-neutral long–short portfolios fully eliminate sector-composition differences, isolating the pricing of trade-network fragility independently of the technology tilt.

Panel A of Table 7 presents the excess returns of the industry-controlled CC portfolios. Two patterns emerge clearly. First, the portfolios continue to exhibit a monotonic increase in excess returns from P0 to P3, indicating that trade vulnerability remains priced even after industry exposures are equalized. Second, the magnitude of the premium is substantially attenuated. The average excess return on P3 declines from 1.71% per month in Table 3 to 1.25% per month after imposing industry control, confirming that part of the original premium reflects the natural overweight of high-technology industries in P3. Consistent with this reduction, both HL30 and HL31 exhibit roughly half of their original long–short spreads, although both remain statistically significant.

Risk-adjusted returns reinforce this conclusion. Under both the CAPM and the Fama–French five-factor model, the most trade-vulnerable portfolio (P3) earns a positive and statistically significant alpha of roughly 0.30% per month, while the industry-neutral HL30 and HL31 factors earn alphas of approximately 0.40% per month. Thus, the trade-vulnerability premium persists even after fully neutralizing industry tilts. These patterns indicate that the premium is not solely an artefact of industry composition: even after aligning industry exposures across portfolios, concentrated sourcing continues to command a positive premium, consistent with a priced component that operates within industries.

To further evaluate the pricing of trade vulnerability in a strict within-industry setting, we construct CC-sorted portfolios separately within each industry. Because the Fama–French 48 classifications produce sparsity—leaving too few firms in many industries to support reliable portfolio formation—we adopt the coarser Fama–French 12 definitions to ensure sufficient cross-sectional granularity. At the end of each month, we sort firms within each FF12 industry into three CC portfolios using industry-specific NYSE breakpoints, and compute the corresponding P1, P2, and P3 returns as well as HL30 and HL31 spreads. We drop industries with fewer than 20 firms—specifically Utilities, Telecommunications, Energy, and Money.[23]

We then aggregate the within-industry CC portfolios across the remaining eight industries

[23] Including these industries yields virtually identical conclusions.

using industry market-value weights to obtain market-wide P1–P3 portfolios and trade-vulnerability factors. This procedure removes all cross-industry variation by construction, ensuring that the estimated pricing effects reflect only within-industry heterogeneity in trade-network concentration.[24]

Panel B of Table 7 reports the within-industry results. The main pricing patterns closely mirror both the global industry-neutral results in Panel A and the baseline evidence in Table 3. The high-vulnerability portfolio P3 continues to earn a sizable premium of roughly 1.7% per month, which remains statistically significant under both the CAPM and the Fama–French five-factor model. More importantly, the within-industry HL30 and HL31 factors earn statistically significant premia of approximately 0.67% per month, robust across alternative pricing models. Overall, the within-industry evidence confirms that the trade-vulnerability premium is not driven by industry tilts but instead reflects economically meaningful heterogeneity in firms' exposure to concentrated global sourcing networks.

5.3.2 Industry Decomposition of the Trade-Vulnerability Premium

Following the industry-controlled analysis, a natural next step is to examine how the trade-vulnerability premium distributes across industries. The industry-controlled tests show that concentrated sourcing commands a risk premium even when sector tilts are held constant, indicating that the underlying trade risk operates at the firm level rather than being driven mechanically by industry composition. Yet industries differ markedly in their integration into global supply chains, suggesting that some sectors may contribute more heavily to the premium than others. We therefore turn to a complementary decomposition that identifies which industries contribute most to the trade-vulnerability premium, providing insight into the economic channels through which global trade risk is priced.

To assess each industry's contribution, we construct HL30 and HL31 factors separately within each Fama–French 12 industry, excluding industries with fewer than 20 firms on average. We also compute industry-level trade metrics—including total import value, total import value from China, the China import ratio, and aggregate country concentration (CC)—by aggregating firm-level measures within each industry.[25] Figure 6 summarizes the results.

Among the eight industries retained in the analysis, the four largest importers by total import value are Manufacturing, Non-Durables, Shops, and Business Equipment. In terms

[24]Results are robust to alternative aggregation methods, including simple averaging across industries and averaging across weighting schemes, both reported in the Robustness section.

[25]Industry-level measures are computed as industry-level aggregates (e.g., total imports, total imports from China, CC).

of exposure to China, however, Business Equipment is the most dependent: it imports approximately $2.8 billion per year on average from China, and its China import ratio—47%—is the highest across all industries. This industry also exhibits the highest aggregate CC at 0.27, indicating a more concentrated sourcing structure than its counterparts.

Consistent with these trade patterns, Business Equipment delivers by far the strongest pricing evidence. The within-industry Fama–French five-factor alphas of HL30 and HL31 are 1.06% and 1.22% per month, respectively, both significant at the 1% level. The alignment between high industry-level CC, elevated China dependence, and large trade-vulnerability premia mirrors the mechanisms documented earlier in Sections 5.1 and 5.2. These results reinforce that industries with concentrated global sourcing—particularly those heavily reliant on Chinese inputs—are the primary contributors to the aggregate trade-vulnerability premium. By contrast, industries with neither high CC nor high China exposure generally fail to produce significant premia, although Health and Chemicals exhibit moderate but statistically significant HL30 spreads.

Overall, the prominence of the Business Equipment industry in driving the premium is consistent with real-economy evidence on the structure of modern global value chains. Business Equipment encompasses computers, electronics, communications equipment, and semiconductor-related goods—sectors repeatedly identified as the most globally integrated and supply-chain-dependent. OECD analyses show that semiconductor and ICT industries rely heavily on geographically concentrated upstream inputs and exhibit pronounced supply-chain fragility (Haramboure et al., 2023). U.S. technology firms source a substantial share of components from China through multi-tier supplier networks (Beeny, 2018; Bethmann et al., 2022), and recent work documents that ICT and electronics industries are among the most exposed to Chinese intermediate goods (Caliendo and Parro, 2023). Against this backdrop, the high CC, elevated China dependence, and large HL30/HL31 premia observed in Business Equipment reflect the structural vulnerability of high-tech value chains. The industry's contribution to the trade-vulnerability premium therefore arises naturally from its concentrated and globally interdependent production structure.

5.4 Trade Vulnerability and the Tech Sector

The industry-controlled analysis establishes that the trade-vulnerability premium is not merely an artefact of sector tilts, while the industry decomposition shows that high-technology industries—especially those in the Business Equipment group—are the primary contributors to this premium. These findings naturally raise a broader asset-pricing question: how does trade vulnerability interact with technology-sector risk? High-tech firms are deeply embedded in globally fragmented supply chains, heavily reliant on concentrated upstream inputs, and disproportionately exposed to China-based production networks. As a result, trade-related disruptions may load heavily on technology-intensive industries, even though the underlying trade-risk premium itself operates at the firm level within industries.

Against this backdrop, an important question is whether the trade-vulnerability factor simply captures technology or "AI" exposure, or whether it represents a distinct priced dimension of global supply-chain fragility to which technology firms are especially sensitive. Put differently, do high-tech firms *drive* the trade-vulnerability premium, or does the trade factor *explain* a component of high-tech returns that reflects their dependence on concentrated and fragile global input networks?

To address this question, we formally examine the interplay between trade and technology risks along two dimensions. First, we test whether standard technology-sector return factors can span or subsume the trade-vulnerability factor. Second, we assess whether the trade factor can account for the average returns on technology and semiconductor portfolios once market exposure is controlled for. This analysis allows us to distinguish whether the trade-vulnerability factor is simply a repackaging of technology-sector performance or whether it prices a broader supply-chain risk—one amplified by the production strategies of high-tech firms, whose global integration boosts efficiency in normal times but leaves them particularly exposed to trade tensions and supply-chain disruptions when these risks materialize.

5.4.1 Robustness Against the Tech Exposure

We begin by examining whether the country-concentration trade-vulnerability factor, R_t^{Trade} (HL30), can be fully captured by technology-sector risk within a standard CAPM-type specification. This question is particularly relevant in light of the preceding analysis. Although the industry-controlled portfolios remove mechanical sector tilts, the most trade-vulnerable firms—especially those in the Business Equipment industry—remain economically tied to high-technology production networks. Thus, it is important to determine whether the trade factor reflects an independent dimension of global supply-chain fragility or whether it is subsumed by exposure to technology-sector performance.

To test whether technology factors can price the trade-vulnerability portfolios and the HL30 factor, we consider a comprehensive set of technology indices intended to span different segments of the tech sector. Specifically, we use the Nasdaq Composite Index (XCMP), the MSCI USA Information Technology Index (MXUST0IT), and the S&P 500 Information Technology Sector Index (S5INFT) as our primary technology factors.[26]

[26]Most indices are obtained from Bloomberg; detailed descriptions and data sources are provided in the Appendix. We also conduct the analysis using additional technology portfolios—such as the Nasdaq-100 ETF (QQQ), the Russell 1000 Technology Index (RGUSTL), the Dow Jones U.S. Total Market Technology Index (DJUSTC), the CRSP U.S. Technology Index (CRSPIT1), and the MSCI World Information Technology

For each technology proxy, we augment the market model with the corresponding technology factor and estimate the following time-series regression for each industry-controlled trade-vulnerability portfolio $i \in \{\mathrm{P0}, \mathrm{P1}, \mathrm{P2}, \mathrm{P3}, \mathrm{HL30}, \mathrm{HL31}\}$:

$$R_t^i = \alpha_i + \beta_i^M (R_t^{\mathrm{Mkt}} - r_{f,t}) + \beta_i^{\mathrm{TC}} R_t^{\mathrm{Tech}} + \varepsilon_t^i, \tag{6}$$

where R_t^i denotes the excess return on portfolio i, $(R_t^{\mathrm{Mkt}} - r_{f,t})$ is the market excess return, and R_t^{Tech} is one of the technology indices listed above. The intercept α_i measures the remaining risk premium after controlling for market and technology exposure, while β_i^{TC} captures the sensitivity of each trade-vulnerability portfolio to technology-sector risk. Because the original CC-sorted portfolios exhibit substantial technology-sector tilts, we focus our analysis on the globally industry-neutral versions of these portfolios to ensure that the results reflect pricing effects rather than mechanical industry composition.[27]

The left panel of Table 8 reports the estimation results. Across all three technology proxies, a consistent pattern emerges in the factor loadings: as trade vulnerability increases from P0 to P3, the technology beta shifts from negative to positive. The negative technology betas for P0 through P2 are statistically significant, indicating that firms with low or moderate trade vulnerability tend to load negatively on technology-sector performance. In contrast, P3 exhibits a positive technology beta, although the loading itself is not statistically significant. At the same time, P3 is the only portfolio that earns a statistically significant alpha—approximately 0.28% per month—with estimates remarkably stable across the three technology factors and significant at the 1% level. These results indicate that while the most trade-vulnerable firms exhibit some comovement with technology-sector returns, their excess returns cannot be explained by technology exposure alone.

The behavior of the trade-vulnerability factors HL30 and HL31 mirrors these portfolio-level findings. After controlling for the market and each technology factor, HL30 (HL31) continues to earn a robust positive risk premium: monthly alphas range from 0.36% (0.26%) to 0.44% (0.30%), all statistically significant across specifications. The trade factors load only mildly on technology, with $\beta_{\mathrm{HL30}}^{\mathrm{TC}}$ ($\beta_{\mathrm{HL31}}^{\mathrm{TC}}$) between 0.17 (0.26) and 0.22 (0.52). Importantly, these modest positive exposures arise primarily because P0 and P1 exhibit significantly negative technology betas, rather than because P3 loads heavily on technology. In other words, the apparent technology exposure of HL30 and HL31 reflects the construction of the long–short portfolios, not a strong inherent technology tilt in P3.

Index (MXWO0IT)—and the results are qualitatively unchanged.

[27] The results are qualitatively unchanged when using the original CC-sorted portfolios or the within-industry neutral portfolios constructed in the previous subsection, indicating that the interplay between trade and technology risk is not sensitive to the choice of industry-neutralization method.

Taken together, these findings show that although trade-vulnerable firms and the trade factors display some association with technology-sector performance, the technology indices do not subsume the trade-vulnerability premium. Instead, the trade factors contribute economically and statistically meaningful pricing information that is distinct from standard technology-sector risk.

To further sharpen the channel, we repeat the analysis using semiconductor-specific factors in place of broad technology indices. In particular, we use the Fama–French Chips industry portfolio, the S&P 500 Semiconductors & Semiconductor Equipment Industry Index (S5SSEQX), and the MSCI ACWI Semiconductors & Semiconductor Equipment Index (MXWD0ST) as semiconductor factors.[28]

The right panel of Table 8 shows that these patterns carry over when we focus on semiconductor indices. Semiconductor betas become increasingly positive as we move from P0 to P3: exposures are significantly negative for P0 and P1, but turn significantly positive for P3. Although the semiconductor betas for P3 are modest in magnitude (0.03 to 0.05), their sign and significance are consistent with the notion that trade-vulnerable firms are connected to semiconductor-related economic activity. Crucially, only P3 and the HL30 (HL31) factors retain significantly positive alphas after controlling for semiconductor factors, indicating that the trade-vulnerability premium persists even when conditioning on this narrow but highly relevant technology segment.

In sum, both the broad technology and semiconductor pricing tests show that the trade-vulnerability portfolios—especially P3—and the trade factors HL30 and HL31 continue to earn positive and significant risk premia after controlling for a wide range of technology and semiconductor risk proxies. These results suggest that the trade-vulnerability factor is not simply a manifestation of a technology or AI-driven cycle. Rather, it prices a distinct dimension of global trade and supply-chain fragility—one that is closely connected to, but not subsumed by, the high-technology sector. Viewed through the lens of the stochastic discount factor, the evidence is consistent with trade- and supply-chain-related shocks constituting a separate state variable in the pricing kernel, to which high-tech firms have large but not exclusive exposure.

5.4.2 Explaining the Tech Performance Using the Trade Risk Factor

Given the significant exposure of the most trade-vulnerable firms to technology-linked industries, a natural question is whether the trade-vulnerability factor can itself serve as a

[28] We also test with the NYSE Semiconductor Index (ICESEMI), the Dow Jones U.S. Total Market Semiconductors Index (DJUSSC), and the Nasdaq Global Semiconductor Index (GSOX). The results are qualitatively unchanged across these alternatives.

key pricing factor for high-tech firms. Technology-intensive sectors—such as semiconductors, business services, and electronics—rely heavily on complex, globally integrated supply chains. Disruptions in these networks, whether triggered by trade policy uncertainty, tariff impositions, or logistical breakdowns, can rapidly propagate through downstream production and affect firm-level productivity, profitability, and stock returns (Bethmann et al., 2022). Because the trade-vulnerability factor R_t^{Trade} reflects compensation for bearing global trade uncertainty and supply-chain shocks, it may account for a component of high-tech sector returns. We therefore test whether HL30 subsumes the risk premium associated with technology portfolios, which would indicate that trade-related risks—rather than purely technology-driven forces—explain part of the recent outperformance of high-tech stocks.

In economic terms, the emergence of a trade-vulnerability risk factor should influence the pricing of technology assets j that depend intensively on global value chains. To formalize this idea, we augment a standard CAPM with the trade-vulnerability factor:

$$R_t^j = \alpha_j + \beta_j^M (R_t^{\text{Mkt}} - r_{f,t}) + \beta_j^{\text{T}} R_t^{\text{Trade}} + \varepsilon_t^j, \tag{7}$$

where R_t^j is the excess return on a given technology asset j, $(R_t^{\text{Mkt}} - r_{f,t})$ is the excess market return, and R_t^{Trade} is the industry-controlled HL30 factor. The key parameters are the intercept α_j, which measures the expected return unexplained by the market and trade factors, and the loading β_j^{T}, which quantifies the exposure of technology portfolios to trade-vulnerability risk.

The left panel of Table 9 reports the empirical results for three broad technology indices. These portfolios earn sizable average excess returns—ranging from 1.23% (XCMP) to 1.57% (S5INFT) per month—consistent with the well-documented strength of the technology sector.[29] Under the CAPM, all indices except the Nasdaq Composite earn significantly positive alphas between 0.45% and 0.51% per month, with t-statistics between 2.28 and 2.52, indicating that the market factor alone cannot explain their performance.

When we augment the model with R_t^{Trade}, the results change markedly. Except the Nasdaq Composite (XCMP), all other technology indices load significantly on the trade-vulnerability factor, with β_j^{T} estimates between 0.51 and 0.58. More importantly, the previously positive CAPM alphas become statistically indistinguishable from zero once HL30 is included. For example, the MSCI USA Information Technology Index (MXUST0IT) and the S&P 500 Information Technology Index (S5INFT) both lose their CAPM significance after controlling for R_t^{Trade}. These findings indicate that HL30 captures the component of technology-sector returns not explained by the market, consistent with the view that high-

[29]For example, the Nasdaq Composite index rose 328.9% between January 2, 2015 and June 27, 2025, increasing from 4,726.81 to 20,273.46.

tech firms earn a premium for bearing global supply-chain risk.

Given this strong performance for broad technology indices, we turn to a more narrowly defined group: semiconductor portfolios. The right panel of Table 9 shows that semiconductor indices earn exceptionally high excess returns—between 1.89% and 2.18% per month—with significant CAPM alphas ranging from 0.66% to 0.91%. After adding HL30, however, these alphas are priced away: none remain statistically significant. At the same time, all semiconductor portfolios load positively and significantly on R_t^{Trade}, with β_j^{T} estimates between 0.61 and 1.06. The average trade-factor beta across the semiconductor portfolios is 0.82, roughly twice the magnitude observed for the broad technology indices. This pattern aligns with the central role of semiconductors in globally fragmented, capacity-constrained supply chains.

Collectively, these results demonstrate that the trade-vulnerability factor is highly effective at explaining excess returns on both broad technology and semiconductor portfolios. In asset-pricing terms, the evidence suggests that a meaningful portion of the elevated returns associated with technology and semiconductor sectors under the CAPM reflects compensation for exposure to global trade and supply-chain risk, rather than mispricing or purely technology-specific forces. This interpretation does not imply that high-tech and AI-oriented firms lack strong fundamentals—indeed, their cash-flow growth is well documented—but rather that their profitability is tightly tied to the smooth functioning of global production networks. Semiconductors and other advanced components represent critical inputs for smartphones, data centers, and industrial electronics, and industry evidence shows that shocks to fabrication capacity, component availability, or logistics have repeatedly caused bottlenecks in downstream sectors (e.g., Bethmann et al., 2022; Wiseman et al., 2025). Firms whose business models rely on these tightly coupled supply chains are therefore especially sensitive to global trade disruptions. Our findings suggest that the trade vulnerability factor (HL30) prices precisely this dimension: it behaves as a traded proxy for a state variable capturing the fragility of global input networks, to which high-technology and semiconductor firms have elevated—but not exclusive—exposure.

5.5 The Evolving Nature of Trade Vulnerability

Over the past decade, global trade risk has not been a fixed background condition but an evolving source of uncertainty. The escalation of the U.S.–China trade war in 2018–2019, the COVID-19 supply-chain disruptions in 2020, and the recent "Liberation Day" tariff package in 2025 have repeatedly shifted investors' beliefs about how vulnerable different parts of the production network are to trade policy shocks. These episodes mark a shift from a world in which trade frictions were viewed as transient disturbances to one in which trade policy risk is persistent, state-dependent, and tied to a broader geopolitical realignment. In such an environment, the burden of trade vulnerability is unlikely to remain concentrated in a fixed set of firms; instead, it can spread outward to a broader set of firms that sit near the frontier of globally integrated supply chains. In this section, we use equity-market volatility to trace how the location and intensity of trade-related risk have changed across firms.

5.5.1 When is the High-CC Portfolios More Volatile?

To examine how trade-related risk evolves over time, we construct daily portfolios and focus on the volatility difference between each trade-vulnerable portfolio and the zero-trade benchmark. For each pair of portfolios $j \in \{\text{P3, P2, P1}\}$ and $P0$, we construct a daily time series of volatility spreads by estimating time-varying portfolio volatilities and computing $\Delta_{j0,t} = \sigma_{j,t} - \sigma_{0,t}$ together with 95% confidence bands.[30]

Figure 7(a) plots the time-series dynamics of the volatility spreads between the three trade-vulnerable portfolios and the zero-trade benchmark. The red line shows $\Delta_{30,t} = \sigma_{\text{P3},t} - \sigma_{\text{P0},t}$, the volatility difference between the most trade-vulnerable firms and the zero-vulnerability portfolio. On average, $\Delta_{30,t}$ is positive and the largest of the three spreads, indicating that firms in P3 consistently bear more return risk than firms in P0. The series also exhibits pronounced spikes around major trade and macro events. The first spike occurs from late 2018 to early 2019, when the initial rounds of the U.S.–China trade war and related negotiations took place. A second spike appears in March 2020, when COVID-19 was declared a national emergency in the United States, and a third spike occurs around the November 2020 presidential election. During the subsequent Biden administration, $\Delta_{30,t}$ remains at an elevated level rather than reverting to its pre-2018 range, and it rises again during 2024 when Trump's campaign and election as the 47th president renew concerns about a more confrontational trade policy.

The blue line shows $\Delta_{20,t} = \sigma_{\text{P2},t} - \sigma_{\text{P0},t}$, the volatility spread for firms with medium trade vulnerability. Before the pandemic, this spread is relatively modest and clearly below $\Delta_{30,t}$. Following COVID-19, however, $\Delta_{20,t}$ increases and begins to move more closely with $\Delta_{30,t}$, indicating that medium-vulnerability firms are increasingly priced as risky relative

[30] Formally, let $r_{j,t}$ and $r_{0,t}$ denote the daily excess returns on portfolio j and $P0$. At each date t we treat $\theta_t = (\mu_{j,t}, \mu_{0,t}, \sigma_{j,t}, \sigma_{0,t}, \text{cov}_{j0,t})'$ as a parameter vector and estimate it by GMM from five moment conditions based on first- and second-order moments: the weighted means of $r_{j,t}$ and $r_{0,t}$, the weighted squared deviations $(r_{j,t} - \mu_{j,t})^2$ and $(r_{0,t} - \mu_{0,t})^2$ relative to $\sigma^2_{j,t}$ and $\sigma^2_{0,t}$, and the weighted cross-product $(r_{j,t} - \mu_{j,t})(r_{0,t} - \mu_{0,t})$ relative to $\text{cov}_{j0,t}$. Moments are formed using all past observations up to t with geometrically decaying weights $w_{t,\tau} \propto \lambda^{t-\tau}$ (with $\lambda = 0.94$). We construct a GMM weighting matrix from a regularized, EWMA-smoothed covariance matrix of these moment conditions and obtain the covariance matrix of $\hat{\theta}_t$. The volatility difference $\Delta_{j0,t} = \sigma_{j,t} - \sigma_{0,t}$ is a smooth function of θ_t, and its pointwise standard error is computed by the delta method.

to the zero-trade benchmark. The most striking episode is the "Liberation Day" tariff announcement: around this event, $\Delta_{20,t}$ spikes and briefly exceeds $\Delta_{30,t}$, suggesting that the associated trade uncertainty is perceived as a broad and more systemic shock. In this episode, the market reprices most sharply the firms at the margin between low and high trade vulnerability—those in P2 that were not previously viewed as the most exposed—rather than only the extreme P3 firms, consistent with a shift from localized to more global trade-policy uncertainty.

The green line plots $\Delta_{10,t} = \sigma_{\mathrm{P1},t} - \sigma_{\mathrm{P0},t}$, the volatility difference between the least vulnerable importers and the zero-trade portfolio. This spread is close to zero and relatively quiet for most of the sample, and only shows a modest uptick around the "Liberation Day" tariffs. The muted behavior of $\Delta_{10,t}$, contrasted with the strong and widening responses of $\Delta_{30,t}$ and especially $\Delta_{20,t}$, reinforces the idea that global trade risk has evolved from a shock borne mainly by a narrow set of highly exposed firms to a more systemic source of risk that increasingly affects firms one step away from the most vulnerable core.

To further assess the evolving nature of trade-vulnerability risk, we compare our volatility-based measure to the text-based trade policy uncertainty (TPU) index of Baker et al. (2016). We obtain the daily TPU index and apply an exponential moving average at a quarterly frequency to smooth high-frequency noise in the news-based series. Figure 7(b) compares the resulting TPU measure with our volatility spreads. In broad terms, the two series comove closely around major trade shocks: both exhibit pronounced spikes during the 2020 pandemic and around the most recent trade-policy episode, the "Liberation Day" tariff shock. At the same time, there are two notable differences that highlight the informational content of our pricing-based measure. First, during the 2018–2019 U.S.–China trade war, $\Delta_{30,t}$ begins to rise as early as September 2018, while the TPU index increases more visibly only in early 2019. Second, $\Delta_{30,t}$ increases during Trump's 2024 campaign and election, whereas the TPU series remains relatively muted on trade policy uncertainty over the same period. These patterns suggest that our volatility-based measure reacts more promptly to shifts in perceived trade risk and is, in some episodes, forward-looking relative to the text-based TPU index, consistent with investors incorporating information about future adverse trade-policy states into prices before these risks are fully reflected in news-based measures.

5.5.2 The Performance of High-CC Portfolios on Liberation Day

Motivated by the rising volatility of medium-vulnerability firms in early 2025, we next study how the portfolios are repriced around the "Liberation Day" tariff episode. We estimate Fama–French five-factor betas for P1, P2, and P3 using daily data in 2024, and compute cumulative abnormal returns (CAR) from January 2, 2025 through June 30, 2025 as the cumulative risk-adjusted returns from these pre-2025 factor models. Figure 8 plots the resulting CAR series. Around the April 2 "Liberation Day" announcement, we observe a clear two-layer pricing response. Medium-vulnerability firms in P2 experience the largest negative impact: their CAR drops sharply on April 3 and continues to decline through April 8. Low-vulnerability importers in P1 also decline over this window, but the magnitude of their underperformance is much smaller. By contrast, the most trade-vulnerable firms in P3 fall on April 2 but then partly recover over the following days, so that by April 8 their CAR is above that of P2.

The pattern changes sharply on April 9, the "Reciprocal Day" when the administration announces that the differential tariffs on trade-surplus countries introduced on April 2 will be paused for 90 days, while tariffs on China will be raised to 125% in response to its retaliation. On this date, the CAR of P3 drops abruptly, whereas P1 and P2 rebound and recoup part of their earlier losses. This asymmetric reaction is natural given the portfolios' trade structures. Firms in P1 and P2 are more geographically diversified and do not rely solely or predominantly on Chinese imports; for them, the temporary suspension of broad tariffs is relatively good news, and their more limited China exposure dampens the effect of the higher China tariff. By contrast, P3 contains the most concentrated and China-intensive importers—recall that the high-China segment within P3 earns the largest trade-vulnerability premium in our double-sort analysis—so the 125% tariff on China represents an additional, largely unanticipated blow on top of trade risk that was already priced in earlier episodes. The large negative CAR for P3 on Reciprocal Day is therefore consistent with a second shock that specifically targets the core of the global value chain.

Overall, these dynamics provide multi-layer pricing evidence that echoes the evolving nature of trade vulnerability documented in the volatility spreads. Before "Liberation Day," the market primarily prices trade uncertainty through the most exposed firms in P3. The broad, multi-country tariff shock on April 2 leads investors to reclassify firms in P2—which sit at the margin between low and high trade vulnerability—as part of the risky set, generating the largest incremental underperformance in that group. The subsequent clarification on April 9 that broad tariffs will be temporarily suspended but that China will be subject to much harsher treatment shifts the focus back toward China-intensive firms in P3. In this sense, the event-study evidence shows how the incidence of priced trade risk moves over time from a narrow core of highly vulnerable firms to a wider set of medium-vulnerability firms when trade risk is perceived as global, and then concentrates again on the most China-dependent segment when policy becomes explicitly targeted.

6 Robustness

This section provides a series of robustness tests demonstrating that the pricing evidence for trade vulnerability is not sensitive to measurement choices, industry adjustments, aggregation schemes, or the presence of high-technology sectors.

Original CC versus Industry-Demeaned CC. Our baseline portfolios rely on industry-demeaned CC to ensure that cross-industry differences in import intensity do not mechanically drive the results (Table 3). As a first robustness check, we reconstruct the CC portfolios using the raw (non-demeaned) CC measure. Table A-X shows that the pricing patterns are virtually unchanged: excess returns increase monotonically from P1 to P3, and both HL30 and HL31 earn economically large and statistically significant premia. The magnitudes are only slightly attenuated relative to the industry-demeaned specification, confirming that the trade-vulnerability premium is not an artifact of the demeaning procedure.

Excluding Industries in Within-Industry Sorting. Section 5.3 showed that the trade-vulnerability premium survives stringent industry controls using both global industry-neutral weighting and within-industry portfolio formation. The industry decomposition further revealed that the Business Equipment sector—dominated by high-technology firms—contributes disproportionately to the premium, consistent with real-economy evidence that high-tech industries, and semiconductors in particular, rely heavily on concentrated global sourcing networks. To ensure that the premium is not driven solely by this sector, we re-estimate the within-industry CC portfolios after excluding each of the Fama–French 12 industries one at a time. Tables A-XI–A-XIII report Fama–French five-factor alphas for the resulting portfolios under alternative aggregation schemes. The main pricing results remain intact: HL30 remains positive and statistically significant regardless of which industry is removed. As expected, excluding Business Equipment reduces the magnitude of the premium, but significance is preserved, demonstrating that the trade-vulnerability effect is not solely driven by the high-tech sector.

Alternative Aggregation Schemes. The within-industry analysis in Section 5.3 aggregates industry-level CC portfolios using industry market-value weights. To confirm that our results are not sensitive to this choice, Table A-XIV reports results using (i) equal-weighted averages across industries and (ii) the simple average of the market-value–weighted and equal-weighted schemes. Across all specifications, the pricing implications are unchanged: P3 continues to earn a substantial premium, and HL30 and HL31 remain statistically significant. These results indicate that the trade-vulnerability premium is robust to alternative ways of aggregating portfolios across industries.

Tech–Trade Interplay Using Within-Industry Neutral Portfolios. Finally, we revisit the interplay between trade-vulnerability portfolios and technology-sector indices using the within-industry CC portfolios instead of the globally industry-neutral portfolios employed in Section 5.4. Tables A-XV and A-XVI show that the results are fully consistent with those reported earlier. Although the trade factors retain mild positive correlations with technology and semiconductor indices, including HL30 in the pricing model eliminates the CAPM alphas of the tech portfolios, and the trade-vulnerability factor remains strongly priced. These findings confirm that the explanatory power of HL30 for technology-sector returns persists even when industry effects are removed ex ante.

Overall, the robustness exercises show that the trade-vulnerability premium is highly stable across measurement choices, industry treatments, aggregation schemes, and pricing specifications. These results reinforce the conclusion that concentrated global sourcing captures a distinct and priced dimension of risk in equity markets.

7 Conclusions

This paper studies how the restructuring of global trade over the past two decades has given rise to a new priced source of systematic risk in equity markets. Using granular bill-of-lading data from S&P Panjiva linked to U.S. public firms, we construct a firm-level measure of trade vulnerability based on import-country concentration. Firms that source a large share of their imports from a limited set of countries are more exposed to disruptions in global trade, and we show that this exposure is compensated in the cross-section: firms with concentrated imports in a small set of source countries earn an economically large risk premium of roughly 0.87% per month relative to firms with zero trade exposure. This premium remains significant after controlling for standard asset-pricing factors and subsumes the pricing information in alternative trade-based measures such as supplier and product concentration.

A novel contribution of our analysis is to connect this trade-vulnerability channel to the structure and pricing of high-tech sectors. Firms with high trade vulnerability are disproportionately concentrated in technology-intensive industries, especially semiconductors, which rely on highly fragmented and geographically concentrated supply chains. By decomposing China import exposure within our trade-vulnerability measure, we document that firms combining high country concentration with intensive China sourcing are central to the trade-vulnerability premium. In asset-pricing terms, the trade-vulnerability factor helps explain the excess returns of broad technology and semiconductor portfolios: once we augment the CAPM with our trade factor, the anomalously high alphas of these high-tech portfolios largely disappear, while their loadings on the trade factor are sizable and statistically significant. These results suggest that an important part of what is often interpreted as “tech” or “AI” outperformance can be understood as compensation for bearing concentrated and fragile global supply-chain risk rather than as mispricing or purely technology-specific risk.

We also show that the nature of trade vulnerability is not static but evolves with the global trade-policy environment. A GMM-based measure of time-varying volatility spreads between trade-vulnerable portfolios and a zero-trade benchmark reveals that the risk of highly vulnerable firms spikes around major trade and supply-chain events, including the 2018–2019 U.S.–China trade war, the COVID-19 pandemic, and the 2025 “Liberation Day” tariffs. After COVID-19, volatility spreads for medium-vulnerability firms converge toward those of the most vulnerable firms, indicating that trade risk has broadened from a narrow set of highly exposed firms to a wider segment of the corporate sector at the margin of global integration. An event study around the “Liberation Day” and subsequent “Reciprocal Day” tariff announcements further uncovers a layered pricing response: broad, multi-country tariff shocks primarily depress medium-vulnerability firms, while a later, China-specific escalation delivers an additional blow to the most concentrated and China-dependent importers. Together, these results highlight that trade vulnerability has become a more system-wide risk whose burden shifts across firms as the trade-policy regime changes.

In conclusion, our study suggests that the transition from an era of stable globalization to one marked by recurrent trade tensions, supply-chain disruptions, and geoeconomic competition has elevated global trade vulnerability to a first-order concern for asset pricing. From a policy perspective, our evidence complements recent theoretical work on resilient supply chains by showing that firms’ sourcing decisions—how concentrated their imports are and where—have measurable consequences for the cost of capital. More broadly, as trade policy and geoeconomic strategies continue to evolve, tracking how trade-related risk is reflected in financial markets may offer a useful real-time window into the resilience and fragility of the global production system, and provides a fruitful avenue for future work at the intersection of international trade, production networks, and asset pricing.

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Figure 1: Top Country Import Ratio vs. Import Country Concentration for the U.S.

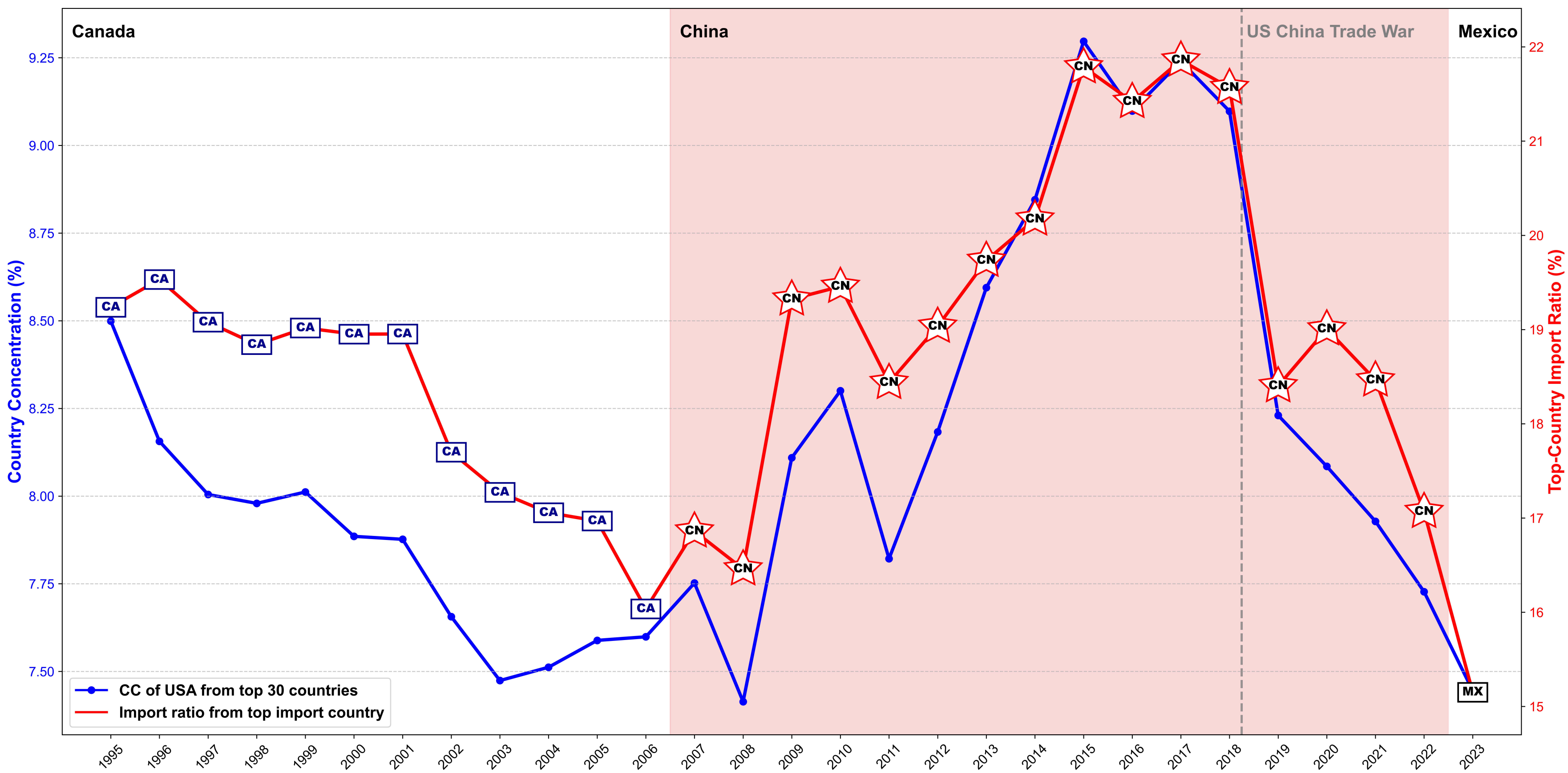

Figure 2: U.S. Import Summary from S&P Panjiva, BEA, and Comtrade

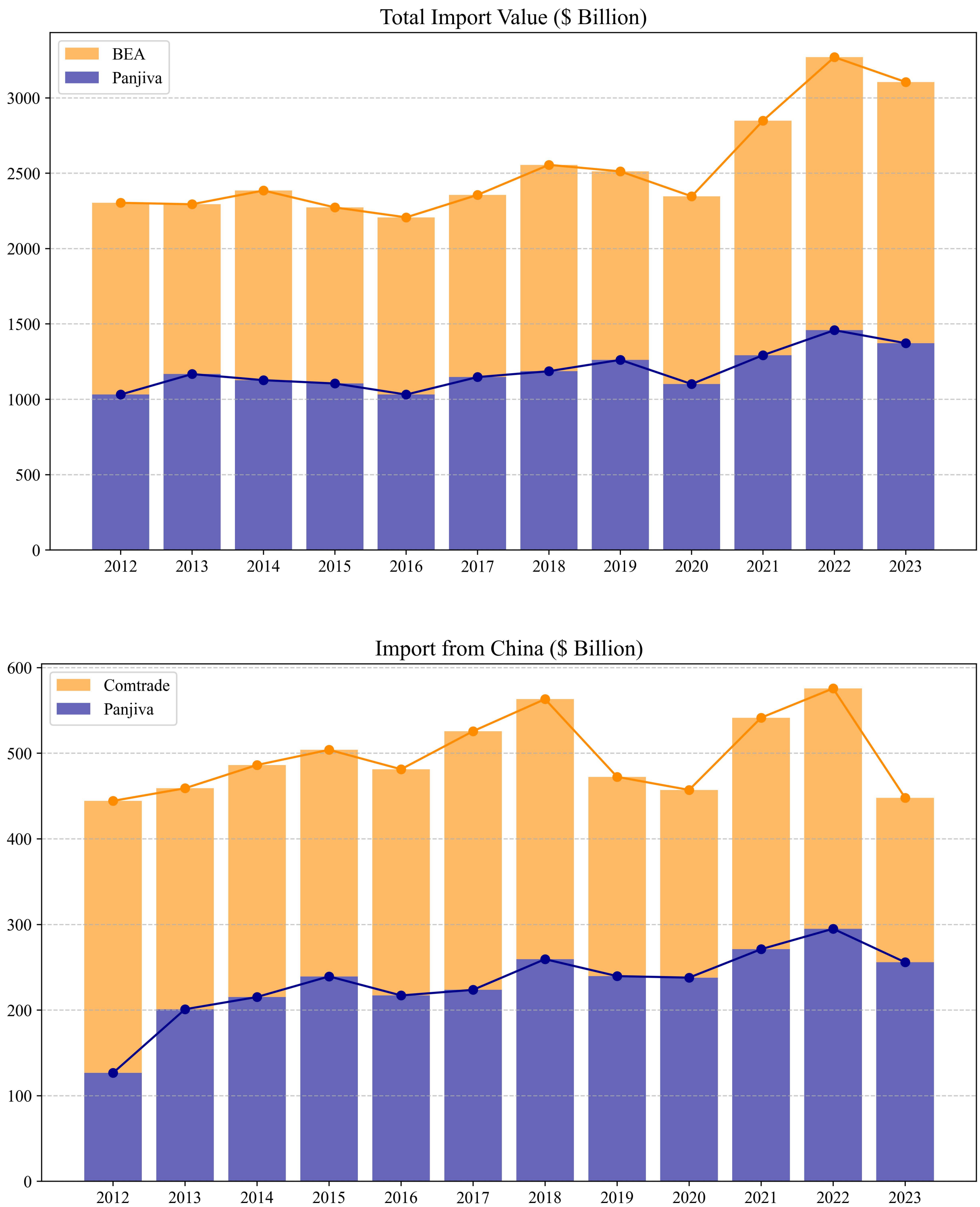

Figure 3(a): Walmart Global Trade Network

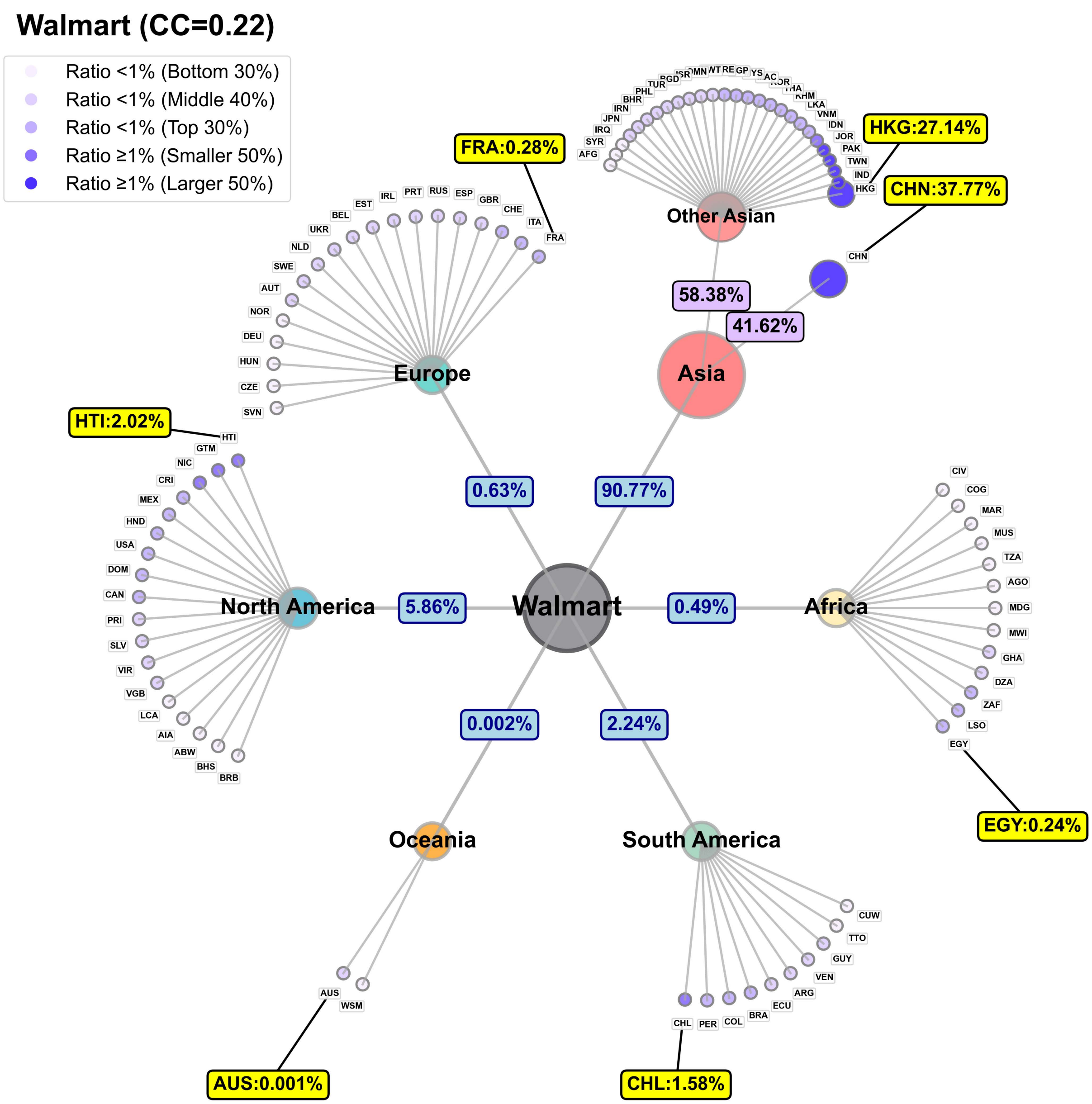

Figure 3(b): Tesla Global Trade Network

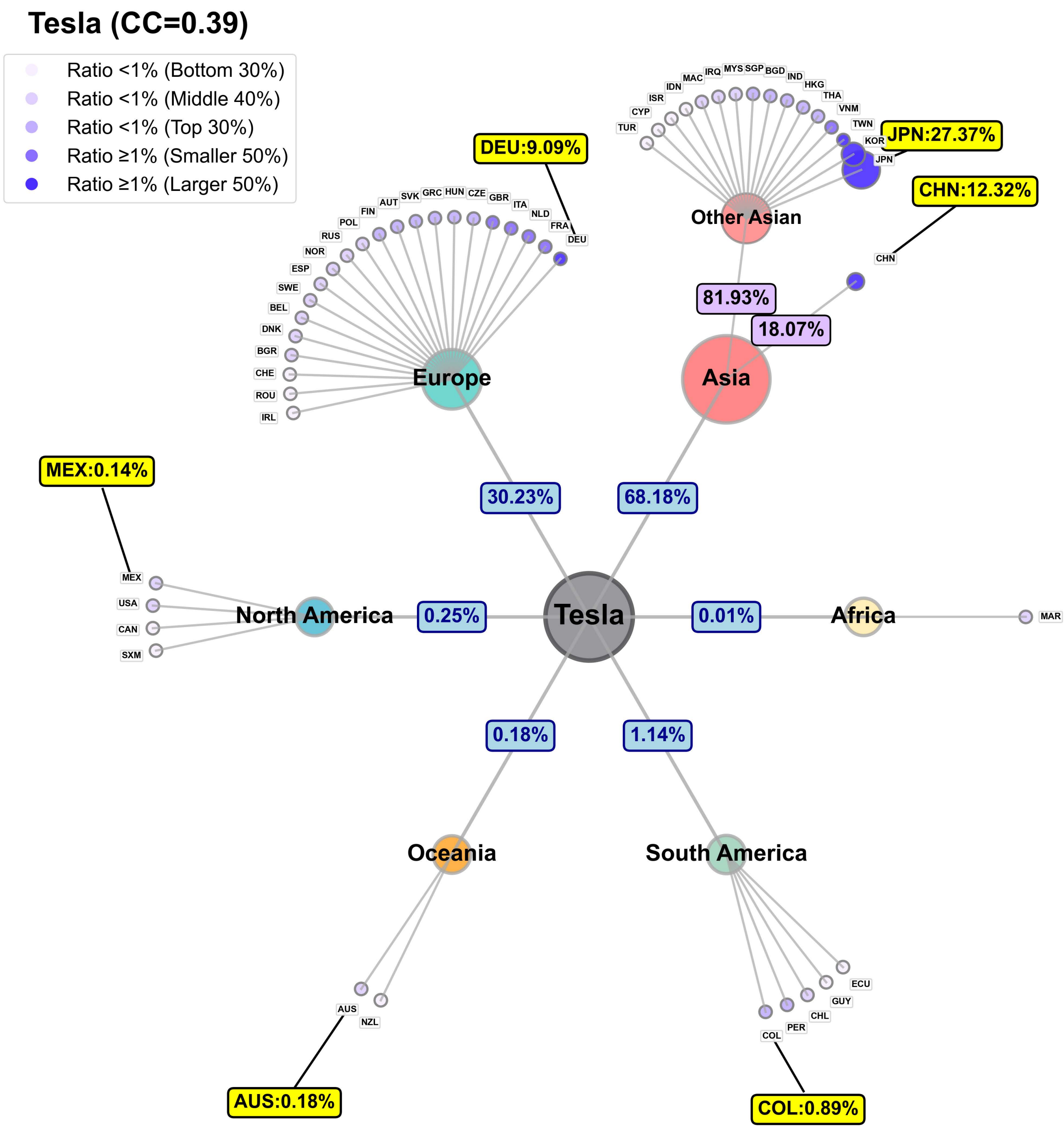

Figure 3(c): Apple Global Trade Network

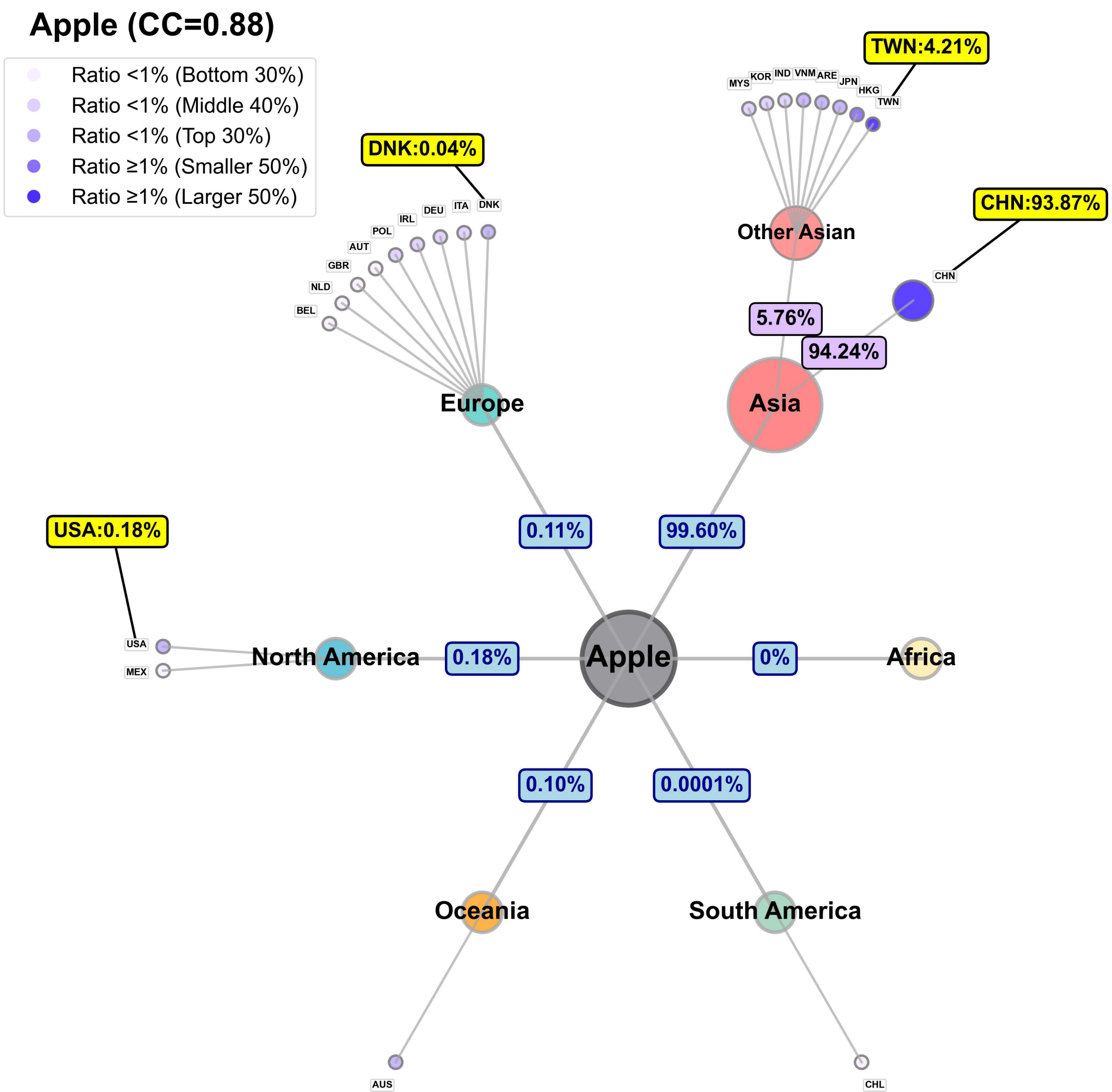

Figure 4: Cumulative Returns of Trade Vulnerability Portfolios against Zero Trade Exposure Portfolio

Figure 5: Industry Beat Exposure of CC-Portfolios and CC × High vs. Low China Portfolios

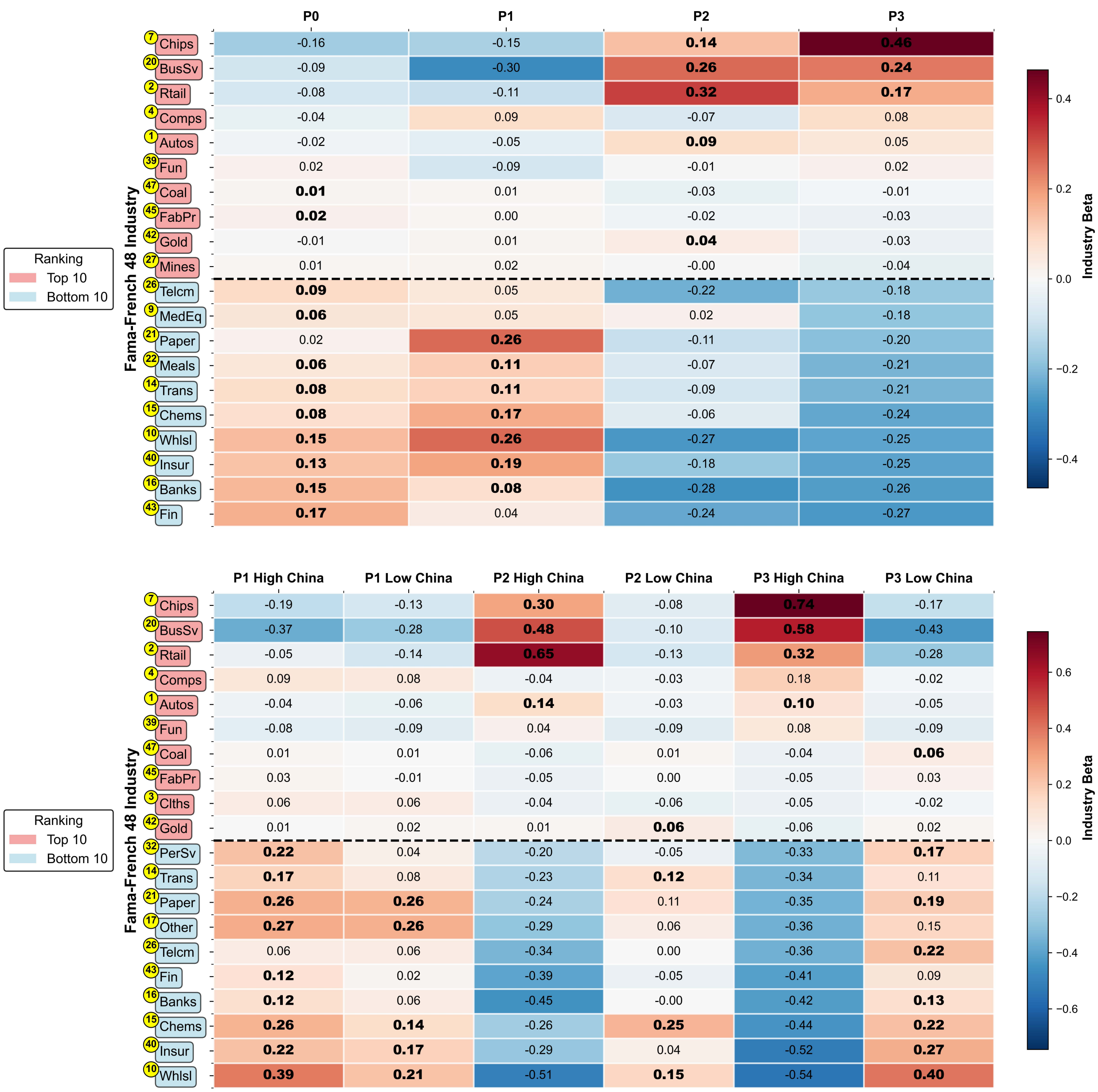

Figure 6: Industry Level Trade and Risk Premium Analysis

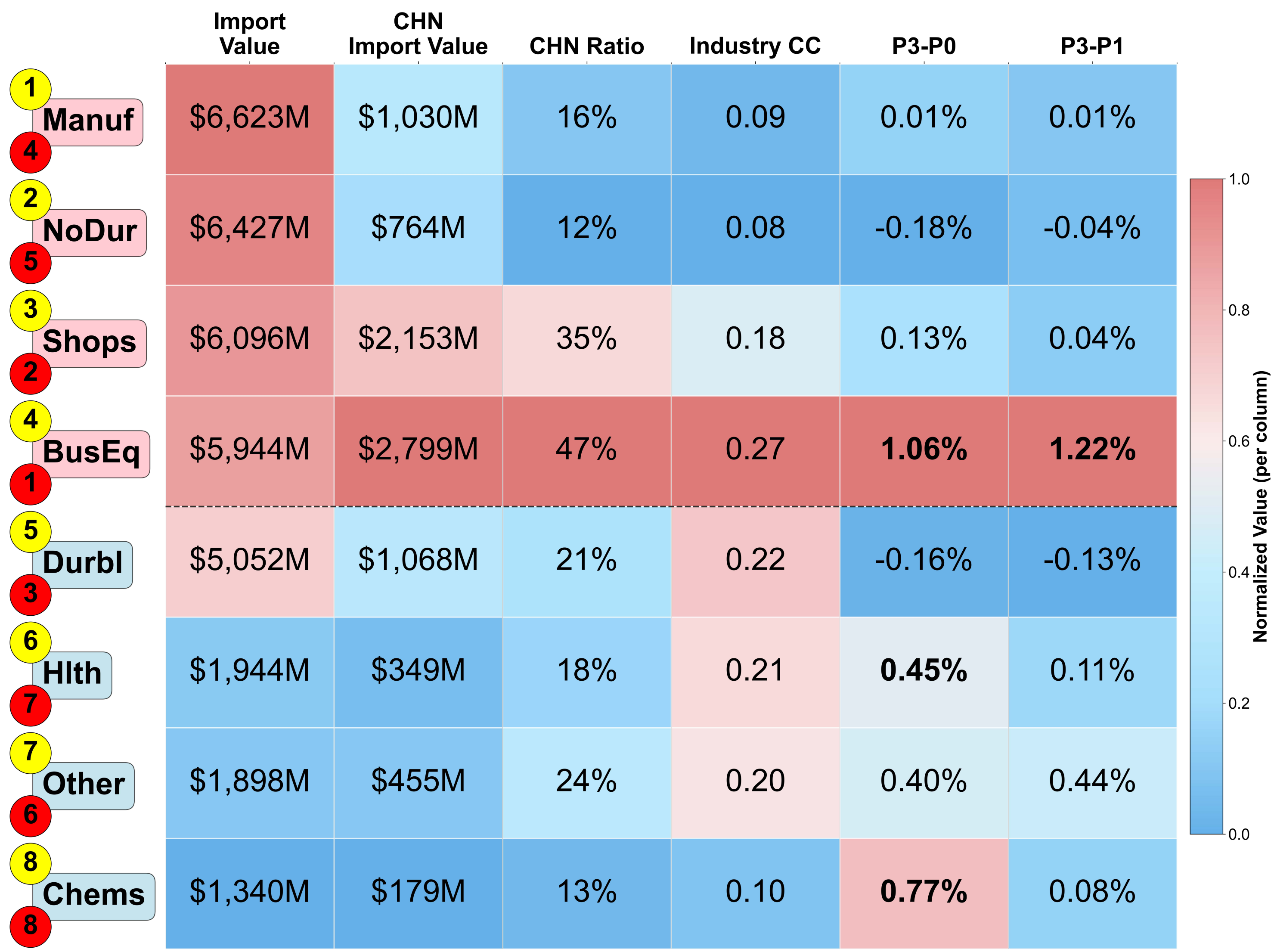

Figure 7(a): Volatility of CC-Portfolios (P1, P2, P3) against The Zero Trade Exposure Portfolio (P0)

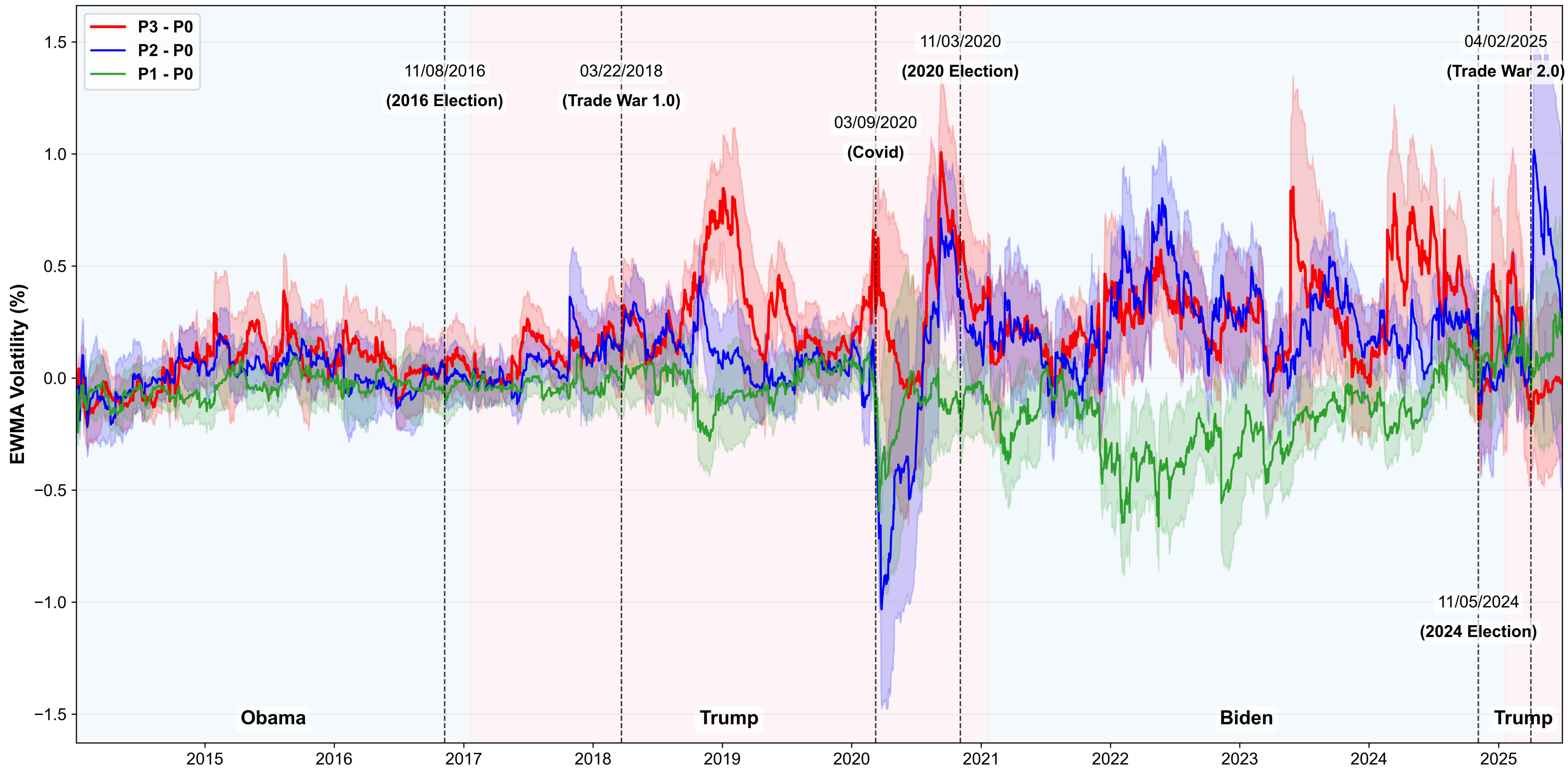

Figure 7(b): Volatility of CC-Portfolios (P1, P2, P3) against The Zero Trade Exposure Portfolio (P0) vs. Trade Policy Uncertainty Index

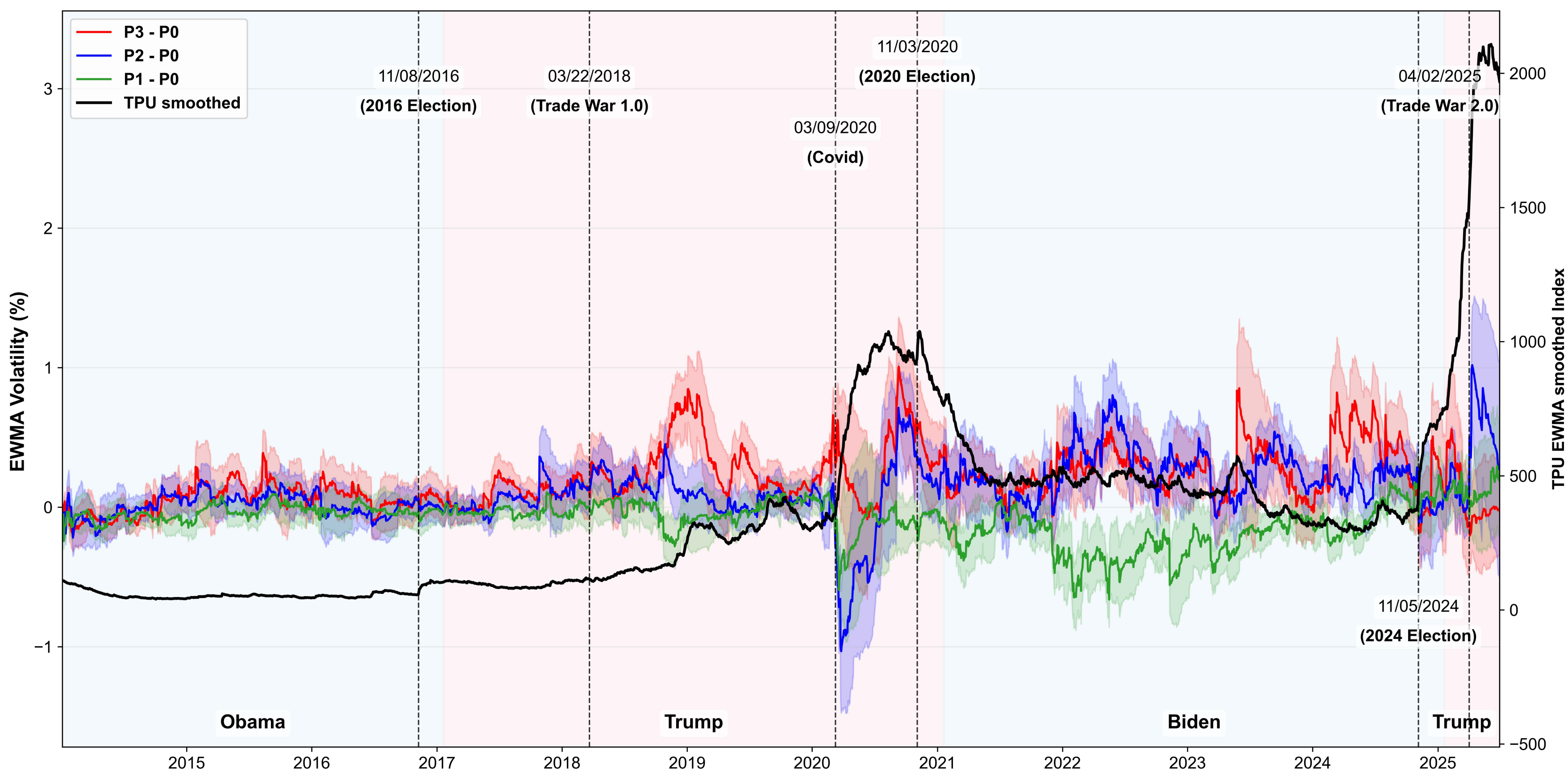

Figure 8: Performance of CC Portfolios on Liberation Day

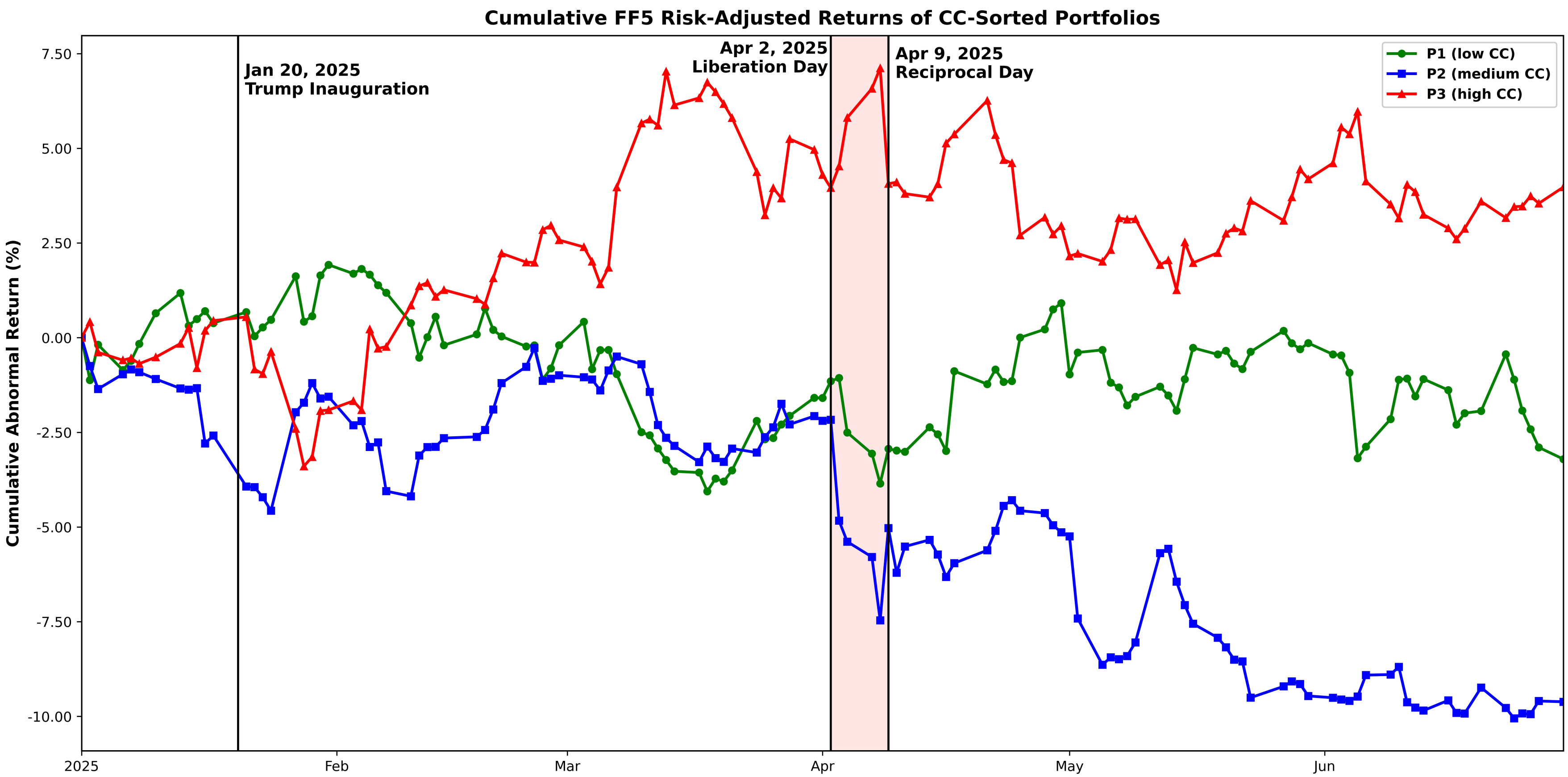

Table 1: Summary Statistics All Sample

This table presents summary statistics for the bill-of-lading data used in our analysis. For each shipment year from 2012 to 2023, we compute the time-series average of year-specific cross-sectional statistics. Import Value denotes the total value of a firm's imports in a given year, aggregated across all shipments. The Import/Revenue ratio is defined as the firm's total import value divided by its total annual revenue. The counts of import countries, suppliers, and HS goods capture the number of distinct origin countries, trading partners, and HS product codes from which a firm imports. The Import Ratio by Location measures the fraction of a firm's total import value sourced from a given geographic area. This statistic is computed conditionally: the ratio is reported only for firm–area pairs with strictly positive import flows.

Trade Variable	**Mean**	**Std**	**P1**	**P25**	**Median**	**P75**	**P99**
Import value (in thousands)	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 by location (%)							
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
Oceana	14.18	28.61	0.00	0.10	0.95	8.56	100

Table 2: Summary Statistics of the CC-Sorted Portfolios

This table reports summary statistics for the trade measures across portfolios sorted on firms' country concentration. Country Concentration (CC) is computed following equation (1). Industry-demeaned Country Concentration is constructed using equation (2). Supplier Concentration and HS2 Goods Concentration are defined analogously to CC, but replace the country dimension with the supplier and product (HS2) dimensions, respectively. Detailed definitions of all measures are provided in the Appendix. Number of Countries, Suppliers, and HS2 Goods denote the counts of distinct origin countries, trading partners, and HS product categories from which a firm imports. Import Value is the total value of a firm's imports in a given year, aggregated across all shipments. The Import/Revenue ratio is the firm's total import value divided by its total annual revenue. Number of Firms reports the number of firms in each portfolio. Market Cap and Revenue represent the average market value and annual revenue of firms within each portfolio. ROA is defined as the ratio of net income to total assets, while Operating Margin is measured as operating income after depreciation divided by sales. All statistics are reported as the time-series average of the cross-sectional mean or median, as indicated.

	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	49.09	28.25	7.54		20.70	10.19	2.90	
Number of HS2 Goods	11.46	7.67	3.79		8.83	5.38	2.13	
Import Value ($ million)	102	71	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	2,190				
Market Cap ($ million)	23,608	23,142	18,333	6,519	3,920	2,421	1,639	1,075
Revenue ($ million)	13,928	9,184	6,711	3,881	3,283	2,023	1,200	581
ROA (%)	5.22	4.49	2.37	-2.24	5.45	5.01	4.36	1.51
Operating Margin (%)	10.48	7.95	-22.93	-98.48	9.95	9.34	8.59	11.91

Table 3: Main Pricing Results of Trade Vulnerability Portfolios by Country Concentration

This table reports the main asset-pricing results for the trade-vulnerability portfolios constructed using firms' import country concentration. The value-weighted portfolios P0 through P3 sort firms from zero trade exposure (P0) to the highest trade vulnerability (P3). The upper panel reports the Pearson correlation matrix between the country-concentration factors (HL30 and HL31) and the Fama–French five factors. HL30 is defined as the high-minus-zero portfolio (P3 − P0), and HL31 is defined as the high-minus-low portfolio (P3 − P1). The middle panel reports the excess returns of the four trade-vulnerability portfolios and the excess returns of the two long–short factors (HL30 and HL31). The lower panel reports the asset-pricing results for each portfolio and each long–short factor under the CAPM and the Fama–French five-factor model. We report risk-adjusted returns (alphas) and factor loadings (betas) estimated from each model. The sample covers January 2014 to June 2025. Newey–West (1987) t-statistics are shown in square brackets.

Person Correlation Matrix						
	HL31	MKT	SMB	HML	RMW	CMA
HL30	0.84	0.14	-0.29	-0.42	0.27	-0.28
HL31	1.00	0.30	-0.03	-0.44	-0.06	-0.45
Pricing Results						
	P0	P1	P2	P3	HL30	HL31
Excess Ret (%)	0.84	0.80	1.03	1.71	0.86	0.90
	[2.78]	[3.05]	[2.82]	[4.50]	[3.74]	[3.46]
CAPM						
α (%)	-0.13	-0.04	0.05	0.65	0.78	0.69
	[-1.83]	[-0.33]	[0.28]	[3.51]	[3.42]	[2.79]
β^{MKT}	1.01	0.87	1.02	1.10	0.09	0.23
	[53.26]	[33.67]	[23.49]	[25.18]	[1.54]	[3.78]
Fama-French Five-Factor						
α (%)	-0.03	-0.11	-0.00	0.52	0.54	0.63
	[-0.46]	[-1.08]	[-0.01]	[3.22]	[2.86]	[2.84]
β^{MKT}	0.98	0.90	1.03	1.09	0.11	0.19
	[88.62]	[32.46]	[24.74]	[28.27]	[2.44]	[3.66]
β^{SMB}	0.08	-0.03	-0.06	-0.03	-0.11	0.00
	[3.13]	[-0.81]	[-1.05]	[-0.46]	[-1.38]	[-0.04]
β^{HML}	0.12	0.09	-0.22	-0.19	-0.31	-0.28
	[4.46]	[1.84]	[-3.60]	[-2.42]	[-3.50]	[-2.38]
β^{RMW}	-0.14	0.22	-0.04	0.26	0.40	0.05
	[-3.99]	[3.28]	[-0.57]	[2.74]	[3.38]	[0.34]
β^{CMA}	-0.09	0.15	0.01	-0.16	-0.07	-0.32
	[-1.88]	[1.68]	[0.08]	[-1.13]	[-0.38]	[-1.53]

Table 4: Alternative Trade Vulnerability Measures and Pricing Results

This table reports the asset-pricing results for trade-vulnerability portfolios constructed using a set of alternative trade measures. Specifically, we consider Supplier Concentration (SC), HS2 Goods Concentration (GC), the inverse of the number of countries (1/NC), the inverse of the number of suppliers (1/NS), and the inverse of the number of HS2 product categories (1/NG). In addition, we examine two value-based measures: the firm's Import/Revenue ratio and its China Ratio, defined as the share of total import value sourced from China in a given shipment year. Panel A reports the risk-adjusted returns (alphas) from the Fama–French five-factor model for the value-weighted portfolios sorted on each alternative trade measure. Panel B compares the CAPM with the CAPM augmented by the country-concentration trade vulnerability factor in pricing the high-minus-zero (P3 − P0) value-weighted portfolios constructed from these alternative measures. The sample covers January 2014 to June 2025. Newey–West (1987) t-statistics are shown in square brackets.

Panel A: 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	-0.1	0.42	0.44	0.36
	[-0.46]	[0.56]	[-0.65]	[2.31]	[2.08]	[1.82]
HS2 Goods Concentration (GC)	-0.03	0.08	-0.01	0.31	0.34	0.24
	[-0.46]	[0.79]	[-0.08]	[1.93]	[1.90]	[1.35]
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	0.25	-0.33	0.42	0.45	0.18
	[-0.46]	[2.34]	[-3.10]	[1.83]	[1.83]	[0.64]
1/Number of HS2 Goods (1/NG)	-0.03	0.18	-0.22	0.22	0.25	0.04
	[-0.46]	[2.11]	[-1.44]	[0.93]	[0.96]	[0.14]
Import/Revenue (Import)	-0.03	0.24	0.13	-0.14	-0.12	-0.39
	[-0.46]	[1.44]	[1.29]	[-1.01]	[-0.71]	[-1.50]
China Ratio (China)	-0.03	0.11	-0.07	0.22	0.25	0.11
	[-0.46]	[0.52]	[-0.60]	[1.54]	[1.40]	[0.40]

Panel B: Pricing for P3 − P0 of Other Trade Measures

Alternative Measures	SC	GC	1/NC	1/NS	1/NG	Import	China
CAPM							
α (%)	0.54	0.41	0.81	0.58	0.41	0.02	0.52
	[2.42]	[2.08]	[2.63]	[2.21]	[1.42]	[0.10]	[2.01]
β^{MKT}	0.06	0.00	0.14	0.18	0.18	-0.10	0.06
	[0.93]	[-0.10]	[1.74]	[2.48]	[2.57]	[-2.41]	[1.02]
Two Factor Model (Market + Trade)							
α (%)	0.00	0.13	0.08	0.02	-0.14	-0.11	-0.09
	[0.02]	[1.04]	[0.56]	[0.13]	[-0.70]	[-0.65]	[-0.58]
β^{MKT}	-0.01	-0.04	0.05	0.11	0.12	-0.11	-0.01
	[-0.15]	[-1.06]	[1.03]	[2.09]	[2.24]	[-2.84]	[-0.23]
β^{T}	0.69	0.36	0.94	0.72	0.71	0.17	0.78
	[6.41]	[3.12]	[9.84]	[5.52]	[5.97]	[2.20]	[7.71]

Table 5: Pricing Results for Portfolios Sorted by Country Concentration × China Import Ratio

This table reports the empirical results from a conditional bivariate portfolio-sorting procedure based on firms' industry-demeaned country concentration (CC) and China Import Ratio, defined as the share of a firm's total import value sourced from China in a given shipment year. We first sort all stocks into three CC portfolios (P1, P2, P3). Within each CC portfolio, we compute the median China Import Ratio and classify firms above the median as High China and those below the median as Low China. Panel A reports the value-weighted excess returns and the average CC level for each double-sorted portfolio. It also reports several portfolio differences: (i) the difference in returns between P3 and P1 from the High-China and Low-China groups; (ii) the difference between High and Low China within each CC portfolio; and (iii) the difference-in-differences measure, defined as (P3 − P1) in High China minus minus (P3 − P1) in Low China. Panel B reports risk-adjusted returns (alphas) from the Fama–French five-factor model for each double-sorted value-weighted portfolio, along with the corresponding factor loadings (betas). The sample covers January 2014 to June 2025. Newey–West (1987) t-statistics are reported in square brackets.

Panel A: Excess Returns and Country Concentration (Industry Demeaned)

Excess Ret (%)	**P1**	**P2**	**P3**	**P3-P1**
High China	0.84	1.28	2.03	1.18
	[2.99]	[2.81]	[4.40]	[3.29]
Low China	0.81	0.74	0.93	0.12
	[3.05]	[2.29]	[3.44]	[0.53]
High-Low China	0.03	0.54	1.10	1.07
	[0.25]	[1.48]	[2.46]	[2.31]

CC	**P1**	**P2**	**P3**	**P3-P1**
High China	-0.30	-0.06	0.27	0.57
	[-111.83]	[-18.97]	[75.43]	[104.41]
Low China	-0.31	-0.05	0.29	0.60
	[-157.36]	[-13.70]	[124.76]	[252.93]
High-Low China	0.01	-0.01	-0.03	-0.03
	[2.01]	[-9.95]	[-6.93]	[-5.05]

Panel B: Fama-French Five-Factor Pricing Results

α **(%)**	**P1**	**P2**	**P3**	**P3-P1**
High China	-0.14	0.06	0.68	0.81
	[-0.94]	[0.31]	[2.90]	[2.59]
Low China	-0.08	-0.08	0.18	0.26
	[-0.76]	[-0.42]	[0.83]	[1.05]
High-Low China	-0.05	0.14	0.50	0.55
	[-0.42]	[0.53]	[1.50]	[1.42]

β^{MKT}	**P1**	**P2**	**P3**	**P3-P1**
High China	0.99	1.19	1.17	0.18
	[25.56]	[18.43]	[18.48]	[2.14]
Low China	0.85	0.86	0.84	-0.01
	[29.45]	[25.38]	[16.17]	[-0.23]
High-Low China	0.14	0.32	0.33	0.19
	[3.66]	[4.07]	[3.12]	[1.65]

β^{SMB}	**P1**	**P2**	**P3**	**P3-P1**
High China	0.05	-0.15	-0.14	-0.19
	[0.76]	[-1.49]	[-1.23]	[-1.16]
Low China	-0.06	0.05	0.27	0.33
	[-1.45]	[0.77]	[3.61]	[3.92]
High-Low China	0.11	-0.19	-0.40	-0.52
	[1.46]	[-1.60]	[-2.57]	[-2.49]

β^{HML}	**P1**	**P2**	**P3**	**P3-P1**
High China	0.10	-0.41	-0.35	-0.45
	[1.42]	[-4.44]	[-2.91]	[-2.56]
Low China	0.10	0.08	0.13	0.03
	[1.96]	[1.11]	[1.19]	[0.28]
High-Low China	0.00	-0.49	-0.48	-0.48
	[-0.03]	[-3.81]	[-2.47]	[-2.19]

β^{RMW}	**P1**	**P2**	**P3**	**P3-P1**
High China	0.19	-0.09	0.34	0.15
	[1.94]	[-0.70]	[2.46]	[0.72]
Low China	0.24	0.06	0.09	-0.15
	[3.52]	[0.94]	[0.94]	[-1.31]
High-Low China	-0.05	-0.15	0.25	0.30
	[-0.61]	[-0.94]	[1.29]	[1.25]

β^{CMA}	**P1**	**P2**	**P3**	**P3-P1**
High China	0.12	0.02	-0.18	-0.30
	[1.29]	[0.10]	[-0.87]	[-1.13]
Low China	0.16	0.02	0.04	-0.13
	[1.70]	[0.13]	[0.28]	[-0.83]
High-Low China	-0.04	0.00	-0.21	-0.17
	[-0.72]	[-0.01]	[-0.85]	[-0.67]

Table 6: Characteristics for Portfolios Sorted by Country Concentration × China Import Ratio

This table reports the empirical results of characteristics from a conditional bivariate portfolio-sorting procedure based on firms' industry-demeaned country concentration (CC) and China Import Ratio, defined as the share of a firm's total import value sourced from China in a given shipment year. We first sort all stocks into three CC portfolios (P1, P2, P3). Within each CC portfolio, we compute the median China Import Ratio and classify firms above the median as High China and those below the median as Low China. We report the average China Ratio, Market Value, Supplier Concentration (SC), HS2 Goods Concentration (GC), Number of Countries (NC), Number of Suppliers (NS), Number of HS2 Goods (NG), and the Import/Revenue Ratio for each of the six double-sorted portfolios. We also present several characteristic differences: (i) the difference in returns between P3 and P1 from the High-China and Low-China groups; (ii) the difference between High and Low China within each CC portfolio; and (iii) the difference-in-differences measure, defined as (P3 − P1) in High China minus minus (P3 − P1) in Low China. The sample covers January 2014 to June 2025. Newey–West (1987) *t*-statistics are reported in square brackets.

China Ratio	P1	P2	P3	P3-P1
High China	0.36	0.51	0.60	0.24
	[80.65]	[61.63]	[39.20]	[18.05]
Low China	0.04	0.03	0.00	-0.04
	[26.39]	[11.44]	[4.20]	[-26.63]
High-Low China	0.32	0.49	0.60	0.28
	[90.43]	[74.72]	[39.34]	[20.13]

Market Value (in millions)	P1	P2	P3	P3-P1
High China	15,081	27,235	26,520	11,439
	[14.45]	[6.87]	[8.49]	[4.56]
Low China	32,081	19,068	10,180	-21,902
	[14.20]	[11.20]	[14.21]	[-12.45]
High-Low China	-17,001	8,167	16,340	33,341
	[-11.01]	[2.54]	[5.50]	[10.10]

SC	P1	P2	P3	P3-P1
High China	-0.29	-0.10	0.20	0.49
	[-116.98]	[-28.41]	[34.88]	[68.19]
Low China	-0.26	-0.02	0.33	0.59
	[-123.35]	[-5.93]	[74.08]	[110.03]
High-Low China	-0.03	-0.08	-0.13	-0.10
	[-9.50]	[-19.07]	[-14.87]	[-9.49]

GC	P1	P2	P3	P3-P1
High China	-0.18	-0.05	0.11	0.29
	[-29.66]	[-16.03]	[39.58]	[37.16]
Low China	-0.14	0.00	0.19	0.33
	[-35.15]	[-0.35]	[55.30]	[50.73]
High-Low China	-0.04	-0.05	-0.08	-0.04
	[-4.20]	[-10.76]	[-17.54]	[-3.84]

NC	P1	P2	P3	P3-P1
High China	12.00	7.75	3.68	-8.32
	[78.70]	[36.47]	[39.47]	[-47.34]
Low China	12.41	6.48	2.30	-10.11
	[65.84]	[41.43]	[61.22]	[-59.75]
High-Low China	-0.42	1.27	1.37	1.79
	[-1.63]	[6.56]	[14.90]	[6.15]

NS	P1	P2	P3	P3-P1
High China	60.05	41.04	11.62	-48.43
	[31.35]	[17.32]	[17.07]	[-21.38]
Low China	38.19	15.53	3.47	-34.72
	[44.82]	[26.13]	[43.65]	[-43.40]
High-Low China	21.86	25.51	8.15	-13.70
	[8.75]	[12.38]	[12.30]	[-4.90]

NG	P1	P2	P3	P3-P1
High China	12.92	9.26	4.85	-8.07
	[47.27]	[47.07]	[60.07]	[-28.16]
Low China	10.01	6.09	2.74	-7.27
	[53.95]	[40.13]	[59.27]	[-44.30]
High-Low China	2.92	3.17	2.12	-0.80
	[8.38]	[16.32]	[22.26]	[-2.31]

Import/Revenue (%)	P1	P2	P3	P3-P1
High China	1.69	1.98	2.08	0.40
	[20.21]	[21.79]	[16.34]	[3.79]
Low China	1.61	2.01	1.49	-0.12
	[20.82]	[19.59]	[18.89]	[-1.10]
High-Low China	0.08	-0.03	0.60	0.52
	[0.85]	[-0.24]	[4.00]	[3.09]

Table 7: Industry-Controlled CC Portfolios

This table reports the pricing results for trade-vulnerability (CC) portfolios constructed using two industry-neutralization approaches: (i) global industry-neutral weighting and (ii) within-industry sorting. Under the global industry-neutral method, we first form CC portfolios based on Fama–French 48 industry-demeaned CC. For each CC portfolio, we compute value-weighted returns for every industry represented in the portfolio and then reweight these industry-level returns using global market-value weights computed from the full sample of Fama–French 48 industries. Because CC portfolios may not span all 48 industries, the long–short factors (HL30 and HL31) are constructed only from the intersection of industries appearing in both legs of the long–short portfolios (P0–P3 or P1–P3) to ensure exact industry neutrality. Under the within-industry sorting method, firms are sorted into CC portfolios separately within each Fama–French 12 industry. We exclude industries with fewer than 20 firms on average (Energy, Telecom, Utilities, and Money). The final CC portfolios are obtained by aggregating the eight remaining industries using global industry market-value weights. Panel A and Panel B report excess returns as well as CAPM and Fama–French five-factor alphas for the global industry-neutral portfolios and the within-industry portfolios, respectively. The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are reported in brackets.

Panel A: Global Industry Neutral Weighting

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
Excess Ret(%)	0.86	0.86	1.04	1.25	0.41	0.40
	[2.74]	[2.85]	[3.10]	[4.01]	[3.91]	[3.16]
α^{CAPM}(%)	-0.15	-0.10	0.05	0.28	0.46	0.39
	[-2.43]	[-1.05]	[0.41]	[2.95]	[4.12]	[3.39]
α^{FF5}(%)	-0.04	-0.06	0.16	0.31	0.38	0.37
	[-0.85]	[-0.75]	[1.29]	[3.74]	[3.93]	[3.09]

Panel B: Within Industry Sorting

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
Excess Ret(%)	1.03	1.03	1.00	1.70	0.67	0.67
	[2.97]	[3.40]	[3.31]	[5.01]	[3.93]	[3.07]
α^{CAPM}(%)	-0.01	0.13	0.05	0.68	0.69	0.56
	[-0.06]	[1.13]	[0.39]	[4.72]	[4.16]	[2.79]
α^{FF5}(%)	0.07	0.08	-0.01	0.63	0.56	0.55
	[0.80]	[0.75]	[-0.11]	[4.35]	[3.52]	[2.71]

Table 8: Tech Exposure of Trade Vulnerability Portfolios

This table reports the technology-exposure regressions for the global industry-neutral trade-vulnerability portfolios and factor. For each value-weighted portfolio (P0, P1, P2, P3) and for the high-minus-zero factor (HL30), we estimate technology betas using equation (6). In the left panel, we use three broad technology indices as the technology factor: the Nasdaq Composite (XCMP), the MSCI USA Information Technology Index (MXUS0IT), and the S&P 500 Information Technology Index (S5INFT). In the right panel, we use three semiconductor-specific indices as alternative technology proxies: the MSCI ACWI Semiconductors & Semiconductor Equipment Index (MXWD0ST), the S&P 500 Semiconductors & Semiconductor Equipment Industry Index (S5SSEQX), and the Fama–French Chips industry portfolio. For each specification, we report the risk-adjusted return (alpha), the market beta, and the technology-factor beta (β^{TC}), where the factor corresponds to the index listed in the column header. The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are reported in brackets.

Technology Index						
	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
$\alpha(\%)$	-0.12	-0.01	0.07	0.28	0.44	0.30
	[-1.92]	[-0.17]	[0.56]	[3.01]	[3.72]	[2.45]
β^{MKT}	1.04	1.00	1.02	1.01	-0.05	0.01
	[66.06]	[30.46]	[44.94]	[30.38]	[-1.50]	[0.27]
XCMP	-0.18	-0.54	-0.11	-0.02	0.10	0.52
	[-3.10]	[-7.29]	[-1.18]	[-0.29]	[1.10]	[4.64]
$\alpha(\%)$	-0.06	0.02	0.14	0.27	0.38	0.26
	[-1.07]	[0.23]	[1.08]	[2.90]	[3.20]	[2.26]
β^{MKT}	1.04	1.00	1.02	1.01	-0.05	0.01
	[83.12]	[29.34]	[49.54]	[29.92]	[-1.44]	[0.27]
MXUS0IT	-0.2	-0.27	-0.19	0.01	0.18	0.28
	[-6.23]	[-4.91]	[-3.13]	[0.26]	[4.53]	[3.98]
$\alpha(\%)$	-0.04	0.02	0.14	0.27	0.36	0.26
	[-0.85]	[0.27]	[1.12]	[2.90]	[3.13]	[2.21]
β^{MKT}	1.04	1.00	1.02	1.01	-0.05	0.01
	[86.67]	[29.27]	[49.42]	[29.90]	[-1.43]	[0.27]
S5INFT	-0.21	-0.25	-0.18	0.01	0.18	0.26
	[-7.03]	[-5.00]	[-2.98]	[0.29]	[4.77]	[3.96]

Semiconductor Index						
	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
$\alpha(\%)$	-0.12	-0.06	0.05	0.26	0.42	0.33
	[-2.09]	[-0.63]	[0.44]	[2.72]	[3.86]	[2.96]
β^{MKT}	1.04	1.00	1.02	1.01	-0.05	0.01
	[66.86]	[30.60]	[42.84]	[29.01]	[-1.50]	[0.28]
MXWD0ST	-0.05	-0.06	0.00	0.03	0.06	0.09
	[-2.39]	[-2.18]	[-0.06]	[1.56]	[2.51]	[2.53]
$\alpha(\%)$	-0.1	-0.06	0.07	0.25	0.40	0.31
	[-1.90]	[-0.55]	[0.53]	[2.59]	[3.72]	[2.76]
β^{MKT}	1.04	1.00	1.02	1.01	-0.05	0.01
	[67.07]	[30.72]	[43.83]	[28.81]	[-1.48]	[0.28]
S5SSEQX	-0.05	-0.05	-0.01	0.03	0.07	0.08
	[-2.88]	[-2.09]	[-0.41]	[1.75]	[2.75]	[2.60]
$\alpha(\%)$	-0.05	0.00	0.13	0.24	0.33	0.24
	[-0.96]	[0.01]	[0.95]	[2.43]	[2.98]	[2.14]
β^{MKT}	1.04	1.00	1.02	1.01	-0.05	0.01
	[77.91]	[30.65]	[45.36]	[28.82]	[-1.44]	[0.27]
Chips	-0.12	-0.13	-0.09	0.05	0.16	0.19
	[-5.17]	[-3.96]	[-2.55]	[2.43]	[5.80]	[4.68]

Table 9: Pricing the Tech Performance using the Trade Risk Factor

This table reports the pricing results for the global industry-neutral trade-vulnerability factor applied to technology portfolios. For each technology index, we estimate the two-factor model in equation (7). We employ three broad technology indices as technology-portfolio proxies—the Nasdaq Composite (XCMP), the MSCI USA Information Technology Index (MXUS0IT), and the S&P 500 Information Technology Index (S5INFT). As alternative proxies, we also consider three semiconductor indices: the MSCI ACWI Semiconductors & Semiconductor Equipment Index (MXWD0ST), the S&P 500 Semiconductors & Semiconductor Equipment Industry Index (S5SSEQX), and the Fama–French Chips industry portfolio. As a benchmark, we additionally report CAPM estimates for each technology portfolio. The left panel presents results based on the broad technology indices, and the right panel presents results based on the semiconductor indices. The upper panel reports the average excess returns of each technology portfolio. The middle panel reports the CAPM estimates. The lower panel reports the results from the two-factor model in equation (7). For each specification, we report the risk-adjusted return (alpha), the market beta, and the trade-factor beta (β^T). The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are shown in brackets.

Technology Index			
	XCMP	MXUS0IT	S5INFT
Excess Ret(%)	1.23	1.53	1.57
	[3.32]	[3.98]	[4.18]
CAPM			
α(%)	0.17	0.45	0.51
	[1.06]	[2.28]	[2.52]
β^{MKT}	1.1	1.11	1.1
	[30.53]	[22.15]	[20.59]
Two Factor Model (Market + Trade)			
α(%)	0.12	0.22	0.25
	[0.68]	[1.01]	[1.11]
β^{MKT}	1.10	1.14	1.12
	[29.40]	[20.86]	[19.51]
β^{T}	0.12	0.51	0.58
	[1.07]	[5.05]	[5.41]

Semiconductor Index			
	MXWD0ST	S5SSEQX	Chips
Excess Ret(%)	1.89	2.18	1.97
	[3.13]	[3.55]	[4.12]
CAPM			
α(%)	0.66	0.91	0.8
	[1.81]	[2.24]	[2.76]
β^{MKT}	1.27	1.32	1.22
	[10.74]	[9.84]	[16.77]
Two Factor Model (Market + Trade)			
α(%)	0.38	0.55	0.31
	[1.07]	[1.47]	[1.08]
β^{MKT}	1.3	1.35	1.25
	[10.67]	[9.73]	[16.24]
β^{T}	0.61	0.78	1.06
	[2.68]	[2.71]	[5.67]

8 Appendix

8.1 Alternative Trade Measures

Supplier Concentration: For firm i in a shipment year t, let $I_{i,s,t}$ denote the import value from supplier s, and let

$$I_{i,t} = \sum_{s} I_{i,s,t}$$

be the total import value across all suppliers. Define the supplier import share as

$$s_{i,s,t} = \frac{I_{i,s,t}}{I_{i,t}}.$$

Then the *firm-level supplier import concenration* is

$$SC_{i,t} = \sum_{s} (s_{i,s,t})^2 = \sum_{s} \left(\frac{I_{i,s,t}}{I_{i,t}} \right)^2.$$

Interpretation: A higher $SC_{i,t}$ means the firm is more reliant on a few suppliers, which increases its vulnerability to counterparty-specific disruptions. A lower value indicates more diversification across suppliers.

Goods Concentration: For firm i in a shipment year t, let $I_{i,g,t}$ denote the import value of HS2 goods g, and let

$$I_{i,t} = \sum_{g} I_{i,g,t}$$

be the total import value across all HS2 goods categories. Define the HS2 goods import share as

$$s_{i,g,t} = \frac{I_{i,g,t}}{I_{i,t}}.$$

Then the *firm-level HS2-goods import concentration* is

$$GC_{i,t} = \sum_{g} (s_{i,g,t})^2 = \sum_{g} \left(\frac{I_{i,g,t}}{I_{i,t}} \right)^2.$$

Interpretation: A higher $GC_{i,t}$ indicates that the firm's imports are concentrated in a narrow range of product categories, exposing it to product-specific input bottlenecks. A lower value reflects greater diversification across input types.

Other Trade Variables: Let i index firms and t index years. Let $\text{ImportValue}_{itcjh}$ denote the import value for firm i in year t, from country c, supplier j, and HS2 product h.

Total Import Value:

$$\text{TIV}_{it} = \sum_{c,j,h} \text{ImportValue}_{itcjh}$$

Import-to-Revenue Ratio:

$$\text{ImpRevRatio}_{it} = \frac{\text{TIV}_{it}}{\text{Revenue}_{it}}$$

Number of Countries (unique):

$$\text{NumCountry}_{it} = |\{c : \text{ImportValue}_{itc} > 0\}|$$

Number of Suppliers (unique):

$$\text{NumSupplier}_{it} = |\{j : \text{ImportValue}_{itj} > 0\}|$$

Number of HS2 Goods (unique):

$$\text{NumHS2}_{it} = |\{h : \text{ImportValue}_{ith} > 0\}|$$

8.2 Sourcing Information of Technology Index

Nasdaq Composite Index (XCMP): Downloaded from Fed ST. LOUIS.

MSCI USA Information Technology Index (MXUS0IT) : Downloaded from Bloomberg.

S&P 500 Information Technology Sector GICS Level 1 Index (S5INFT) : Downloaded from Bloomberg.

8.3 Sourcing Information of Semiconductor Index

MSCI ACWI Semiconductors & Semiconductor Equipment Index (MXWD0ST) : Downloaded from Bloomberg.

S&P 500 Semiconductors & Semiconductor Equipment Industry Group GICS 2 Index (S5SSEQX) : Downloaded from Bloomberg.

Chips : Downloaded from Kenneth R. French - Data Library

Table A-X: Main Pricing Results of Trade Vulnerability Portfolios by Original Country Concentration

This table reports the main asset-pricing results for the trade-vulnerability portfolios constructed using firms' import country concentration. The value-weighted portfolios P0 through P3 sort firms from zero trade exposure (P0) to the highest trade vulnerability (P3) based on the firm's original country-concentration measure. The upper panel reports the excess returns of the four trade-vulnerability portfolios and the excess returns of the two long–short factors (HL30 and HL31). The middle and lower panels present the corresponding asset-pricing results under the CAPM and the Fama–French five-factor model, respectively. For each portfolio and each long–short factor, we report risk-adjusted returns (alphas) and factor loadings (betas) estimated from the model. The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are shown in brackets.

	P0	P1	P2	P3	HL30	HL31
Pricing Results						
Excess Ret (%)	0.84	0.8	0.95	1.67	0.83	0.87
	[2.78]	[2.79]	[2.83]	[4.30]	[3.44]	[3.30]
CAPM						
α (%)	-0.13	-0.05	-0.06	0.66	0.79	0.71
	[-1.83]	[-0.45]	[-0.39]	[3.48]	[3.38]	[2.94]
β^{MKT}	1.01	0.87	1.05	1.04	0.04	0.17
	[53.26]	[25.44]	[24.83]	[32.99]	[0.85]	[3.33]
Fama-French Five-Factor						
α (%)	-0.03	-0.12	-0.09	0.5	0.52	0.62
	[-0.46]	[-1.00]	[-0.70]	[3.10]	[2.76]	[2.60]
β^{MKT}	0.98	0.9	1.04	1.06	0.08	0.16
	[88.62]	[25.26]	[23.25]	[32.87]	[2.16]	[3.07]
β^{SMB}	0.08	-0.03	-0.03	-0.08	-0.16	-0.05
	[3.13]	[-0.84]	[-0.52]	[-1.14]	[-1.99]	[-0.58]
β^{HML}	0.12	0.07	-0.16	-0.23	-0.35	-0.3
	[4.46]	[1.17]	[-2.71]	[-3.30]	[-4.40]	[-2.48]
β^{RMW}	-0.14	0.20	-0.03	0.28	0.41	0.07
	[-3.99]	[2.64]	[-0.31]	[3.13]	[3.79]	[0.50]
β^{CMA}	-0.09	0.17	-0.11	-0.02	0.07	-0.19
	[-1.88]	[1.65]	[-0.74]	[-0.16]	[0.53]	[-1.07]

Table A-XI: Excluding Industry Tests for Industry-Controlled Vulnerability Portfolios (Value-Weighted)

This table reports the pricing results for the trade-vulnerability portfolios constructed from the within-industry sorting method. Firms are sorted into three CC portfolios within each Fama–French 12 industry, and the final CC portfolios are obtained by aggregating the eleven remaining industries using global industry market-value weights. Each panel reports the Fama–French five-factor risk-adjusted returns for the CC portfolios when excluding the industry listed in the panel. The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are reported in brackets.

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**		**P0**	**P1**	**P2**	**P3**	**HL30**	**HL31**
BusEq	-0.01	0.06	-0.12	0.28	0.29	0.2	**Money**	0.01	0.03	-0.09	0.56	0.55	0.53
	[-0.17]	[0.62]	[-0.97]	[2.59]	[2.89]	[1.50]		[0.17]	[0.25]	[-0.76]	[3.88]	[3.52]	[2.72]
Chems	0.09	0.08	-0.07	0.59	0.5	0.5	**Nodur**	0.07	0.09	-0.07	0.61	0.54	0.5
	[1.11]	[0.88]	[-0.59]	[4.35]	[3.41]	[2.64]		[0.88]	[0.97]	[-0.54]	[4.55]	[3.83]	[2.65]
Drubl	0.07	0.09	-0.09	0.59	0.53	0.5	**Other**	0.07	0.09	-0.04	0.59	0.52	0.49
	[0.85]	[0.94]	[-0.71]	[4.63]	[3.83]	[2.75]		[0.87]	[0.93]	[-0.30]	[4.09]	[3.43]	[2.51]
Enrgy	0.09	0.11	-0.07	0.6	0.51	0.48	**Shops**	0.05	0.06	-0.16	0.62	0.56	0.55
	[1.16]	[1.08]	[-0.62]	[4.64]	[3.47]	[2.61]		[0.73]	[0.61]	[-1.21]	[4.41]	[3.80]	[2.79]
Hlth	0.05	0.04	-0.11	0.56	0.51	0.51	**Telcm**	0.07	0.08	-0.03	0.59	0.52	0.5
	[0.61]	[0.41]	[-0.92]	[3.88]	[3.26]	[2.50]		[0.94]	[0.82]	[-0.27]	[4.91]	[3.97]	[2.77]
Manuf	0.06	0.08	-0.07	0.6	0.54	0.51	**Utils**	0.05	0.09	-0.09	0.57	0.51	0.48
	[0.80]	[0.84]	[-0.57]	[4.24]	[3.40]	[2.56]		[0.69]	[0.92]	[-0.74]	[4.21]	[3.53]	[2.53]

Table A-XII: Excluding Industry Tests for Industry-Controlled Vulnerability Portfolios (Equal-Weighted)

This table reports the pricing results for the trade-vulnerability portfolios constructed using the within-industry sorting method. Firms are first sorted into three CC portfolios within each Fama–French 12 industry, and the final CC portfolios are obtained by aggregating the eleven remaining industries using equal industry weights. Each panel reports the Fama–French five-factor risk-adjusted returns for the CC portfolios when excluding the industry indicated in the panel. The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are reported in brackets.

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
BusEq	-0.09	-0.07	-0.11	0.21	0.3	0.26
	[-1.10]	[-0.53]	[-0.98]	[1.64]	[2.63]	[1.55]
Chems	0.01	-0.05	-0.06	0.34	0.33	0.36
	[0.18]	[-0.36]	[-0.55]	[2.37]	[2.40]	[2.03]
Drubl	-0.03	-0.02	-0.17	0.38	0.41	0.38
	[-0.37]	[-0.18]	[-1.59]	[3.15]	[3.69]	[2.34]
Enrgy	-0.03	-0.02	-0.12	0.34	0.37	0.33
	[-0.38]	[-0.17]	[-0.93]	[2.46]	[2.55]	[1.96]
Hlth	-0.07	-0.1	-0.12	0.29	0.36	0.36
	[-0.97]	[-0.70]	[-1.05]	[2.17]	[2.76]	[1.92]
Manuf	-0.07	-0.07	-0.09	0.33	0.4	0.37
	[-0.96]	[-0.49]	[-0.73]	[2.38]	[2.90]	[2.00]

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
Money	-0.09	-0.09	-0.1	0.27	0.36	0.34
	[-1.15]	[-0.64]	[-1.01]	[2.00]	[2.83]	[1.89]
Nodur	-0.05	-0.04	-0.08	0.36	0.41	0.37
	[-0.69]	[-0.28]	[-0.70]	[2.84]	[3.40]	[2.07]
Other	-0.06	-0.06	-0.07	0.3	0.36	0.33
	[-0.79]	[-0.42]	[-0.56]	[2.15]	[2.77]	[1.82]
Shops	-0.07	-0.07	-0.16	0.32	0.38	0.37
	[-0.90]	[-0.60]	[-1.29]	[2.29]	[2.89]	[2.09]
Telcm	-0.03	-0.01	0.02	0.29	0.32	0.27
	[-0.45]	[-0.05]	[0.14]	[2.61]	[3.79]	[1.88]
Utils	-0.08	-0.04	-0.1	0.28	0.36	0.32
	[-1.16]	[-0.40]	[-1.01]	[2.02]	[2.70]	[1.85]

Table A-XIII: Excluding Industry Tests for Industry Neutral Vulnerability Portfolios (Average Weighting)

This table reports the pricing results for the trade-vulnerability portfolios constructed using the within-industry sorting method. Firms are first sorted into three CC portfolios within each Fama–French 12 industry, and the final CC portfolios are obtained by averaging the CC portfolios aggregated across the eleven remaining industries using both value-weighted and equal-weighted industry weights. Each panel reports the Fama–French five-factor risk-adjusted returns for the CC portfolios when excluding the industry indicated in the panel. The sample spans January 2014 to June 2025. Newey–West (1987) *t*-statistics are reported in brackets.

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
BusEq	-0.05	-0.01	-0.12	0.24	0.29	0.23
	[-0.68]	[-0.05]	[-1.02]	[2.15]	[2.91]	[1.63]
Chems	0.05	0.02	-0.06	0.46	0.41	0.43
	[0.73]	[0.18]	[-0.61]	[3.51]	[3.05]	[2.52]
Drubl	0.02	0.03	-0.13	0.49	0.47	0.44
	[0.28]	[0.36]	[-1.18]	[4.20]	[4.00]	[2.79]
Enrgy	0.03	0.04	-0.1	0.47	0.44	0.41
	[0.40]	[0.42]	[-0.84]	[3.75]	[3.16]	[2.46]
Hlth	-0.01	-0.03	-0.12	0.42	0.43	0.43
	[-0.13]	[-0.25]	[-1.06]	[3.28]	[3.18]	[2.38]
Manuf	0	0.01	-0.08	0.46	0.47	0.44
	[-0.07]	[0.07]	[-0.70]	[3.51]	[3.29]	[2.45]

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
Money	-0.04	-0.03	-0.1	0.42	0.46	0.43
	[-0.54]	[-0.30]	[-0.97]	[3.15]	[3.35]	[2.49]
Nodur	0.01	0.03	-0.08	0.49	0.48	0.44
	[0.13]	[0.31]	[-0.66]	[3.92]	[3.82]	[2.54]
Other	0	0.02	-0.05	0.44	0.44	0.41
	[0.03]	[0.16]	[-0.45]	[3.34]	[3.29]	[2.35]
Shops	-0.01	-0.01	-0.16	0.47	0.47	0.46
	[-0.09]	[-0.10]	[-1.33]	[3.57]	[3.54]	[2.67]
Telcm	0.02	0.04	-0.01	0.44	0.42	0.39
	[0.27]	[0.39]	[-0.06]	[4.17]	[4.14]	[2.55]
Utils	-0.01	0.02	-0.1	0.42	0.44	0.4
	[-0.22]	[0.25]	[-0.93]	[3.28]	[3.28]	[2.35]

Table A-XIV: Within Industry Sorting of Industry-Controlled Trade Vulnerability Portfolios (Equal-Weighted and Aggregated)

This table reports the pricing results for the trade-vulnerability portfolios constructed using the within-industry sorting method. Firms are first sorted into three CC portfolios within each Fama–French 12 industry. We exclude Utilities, Energy, Telecommunications, and Money because each contains fewer than 20 firms on average. To form the final CC portfolios at the market level, we aggregate the eight remaining industries using two approaches. The upper panel reports results based on CC portfolios aggregated using equal industry weights. The lower panel reports results based on the simple average of the equal-weighted and value-weighted industry-aggregated CC portfolios. For each specification, we report excess returns, CAPM alphas, and Fama–French five-factor alphas. The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are reported in brackets.

Panel A:

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
Excess Ret(%)	0.84	0.98	1.06	1.16	0.32	0.18
	[2.68]	[3.34]	[3.24]	[3.75]	[2.71]	[1.16]
α^{CAPM}(%)	-0.19	0.08	0.07	0.17	0.36	0.09
	[-1.99]	[0.57]	[0.48]	[1.23]	[3.08]	[0.56]
α^{FF5}(%)	-0.08	0.01	0.01	0.23	0.31	0.22
	[-0.91]	[0.10]	[0.09]	[1.95]	[2.61]	[1.31]

Panel B:

	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**
Excess Ret(%)	0.94	1.01	1.03	1.43	0.49	0.42
	[2.87]	[3.40]	[3.36]	[4.52]	[3.62]	[2.53]
α^{CAPM}(%)	-0.1	0.1	0.06	0.43	0.52	0.32
	[-1.12]	[0.85]	[0.48]	[3.65]	[3.94]	[2.02]
α^{FF5}(%)	-0.01	0.05	0	0.43	0.44	0.38
	[-0.07]	[0.42]	[-0.02]	[3.55]	[3.27]	[2.20]

Table A-XV: Tech Exposure of Trade Vulnerability Portfolios by Within Industry Sorting
Value-Weighted Aggregated

This table reports the technology-exposure regressions for the trade-vulnerability portfolios and factor constructed using the within-industry sorting approach and aggregated across industries using value-weighted industry weights. For each value-weighted portfolio (P0, P1, P2, P3) and for the high-minus-zero factor (HL30), we estimate technology betas using the regression specification in equation (6). The left panel reports results using three broad technology indices—the Nasdaq Composite (XCMP), the MSCI USA Information Technology Index (MXUS0IT), and the S&P 500 Information Technology Index (S5INFT). The right panel reports results using three semiconductor-specific indices—the MSCI ACWI Semiconductors & Semiconductor Equipment Index (MXWD0ST), the S&P 500 Semiconductors & Semiconductor Equipment Industry Index (S5SSEQX), and the Fama–French Chips industry portfolio. For each specification, we report the risk-adjusted return (alpha), the market beta, and the technology-factor beta (β^{TC}), where each beta corresponds to the index shown in the column header. The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are reported in brackets.

Technology Index							**Semiconductor Index**						
	P0	**P1**	**P2**	**P3**	**HL30**	**HL31**		**P0**	**P1**	**P2**	**P3**	**HL30**	**HL31**
$\alpha(\%)$	-0.03	0.19	0.03	0.58	0.61	0.39	$\alpha(\%)$	0.01	0.13	0	0.54	0.53	0.41
	[-0.23]	[2.02]	[0.23]	[4.17]	[3.22]	[2.22]		[0.05]	[1.15]	[0.00]	[4.29]	[3.22]	[2.38]
β^{MKT}	1.07	0.94	0.98	1.05	-0.02	0.11	β^{MKT}	1.07	0.94	0.98	1.05	-0.02	0.11
	[51.02]	[33.31]	[36.21]	[28.94]	[-0.47]	[2.43]		[54.28]	[36.22]	[36.78]	[32.48]	[-0.56]	[2.42]
XCMP	0.11	-0.4	0.15	0.6	0.49	1	MXWD0ST	-0.02	0	0.08	0.23	0.24	0.23
	[1.60]	[-3.85]	[1.45]	[3.75]	[2.33]	[4.89]		[-0.71]	[-0.05]	[2.69]	[5.20]	[4.94]	[3.19]
$\alpha(\%)$	0.01	0.18	-0.01	0.52	0.5	0.33	$\alpha(\%)$	0.01	0.13	-0.02	0.5	0.49	0.37
	[0.09]	[1.75]	[-0.06]	[4.38]	[3.02]	[2.27]		[0.09]	[1.21]	[-0.19]	[4.16]	[2.98]	[2.22]
β^{MKT}	1.07	0.94	0.98	1.05	-0.02	0.11	β^{MKT}	1.07	0.94	0.98	1.05	-0.02	0.11
	[54.64]	[34.24]	[35.78]	[30.28]	[-0.53]	[2.43]		[54.32]	[35.89]	[37.30]	[32.09]	[-0.55]	[2.40]
MXUS0IT	-0.04	-0.12	0.14	0.37	0.41	0.49	S5SSEQX	-0.02	-0.01	0.09	0.2	0.22	0.21
	[-0.88]	[-1.67]	[1.91]	[4.66]	[3.88]	[3.95]		[-0.85]	[-0.25]	[2.93]	[5.13]	[5.09]	[3.39]
$\alpha(\%)$	0.03	0.18	-0.02	0.5	0.47	0.32	$\alpha(\%)$	0.04	0.17	-0.01	0.48	0.43	0.31
	[0.21]	[1.71]	[-0.16]	[4.36]	[2.96]	[2.23]		[0.38]	[1.47]	[-0.06]	[4.58]	[3.15]	[2.16]
β^{MKT}	1.07	0.94	0.98	1.05	-0.02	0.11	β^{MKT}	1.07	0.94	0.98	1.05	-0.02	0.11
	[56.00]	[34.32]	[35.61]	[30.78]	[-0.55]	[2.44]		[56.88]	[35.21]	[34.96]	[29.09]	[-0.52]	[2.37]
S5INFT	-0.06	-0.1	0.14	0.36	0.42	0.46	Chips	-0.06	-0.05	0.08	0.26	0.32	0.31
	[-1.49]	[-1.52]	[2.10]	[4.87]	[4.33]	[3.98]		[-2.08]	[-1.06]	[1.80]	[5.02]	[4.93]	[3.93]

Table A-XVI: Pricing the Tech Performance using the Trade Risk Factor by Within Industry Sorting Value-Weighted Method

This table reports the pricing results for the trade-vulnerability portfolios and factor constructed using the within-industry sorting approach and aggregated across industries using value-weighted industry weights, applied to technology portfolios. For each technology index portfolio, we estimate the two-factor model in equation (7). We employ three broad technology indices as technology-portfolio proxies—the Nasdaq Composite (XCMP), the MSCI USA Information Technology Index (MXUS0IT), and the S&P 500 Information Technology Index (S5INFT). As alternative proxies, we also use three semiconductor indices: the MSCI ACWI Semiconductors & Semiconductor Equipment Index (MXWD0ST), the S&P 500 Semiconductors & Semiconductor Equipment Industry Index (S5SSEQX), and the Fama–French Chips industry portfolio. As a benchmark, we also report the corresponding CAPM estimates. The left panel presents results based on the broad technology indices, and the right panel presents results based on the semiconductor indices. The upper panel reports the average excess returns of each technology portfolio, the middle panel reports the CAPM results, and the lower panel reports the two-factor model estimates from equation (7). For each specification, we report the risk-adjusted return (alpha), the market beta, and the trade-factor beta (β^T). The sample spans January 2014 to June 2025. Newey–West (1987) t-statistics are reported in brackets.

Technology Index			
	XCMP	MXUS0IT	S5INFT
Excess Ret(%)	1.23	1.53	1.57
	[3.32]	[3.98]	[4.18]
CAPM			
α(%)	0.17	0.45	0.51
	[1.06]	[2.28]	[2.52]
β^{MKT}	1.1	1.11	1.1
	[30.53]	[22.15]	[20.59]
Two Factor Model (Market + Trade)			
α(%)	0	0.12	0.13
	[-0.02]	[0.62]	[0.71]
β^{MKT}	1.1	1.12	1.11
	[34.08]	[28.13]	[27.07]
β^{T}	0.25	0.49	0.55
	[3.57]	[7.78]	[7.99]

Semiconductor Index			
	MXWD0ST	S5SSEQX	Chips
Excess Ret(%)	1.89	2.18	1.97
	[3.13]	[3.55]	[4.12]
CAPM			
α(%)	0.66	0.91	0.8
	[1.81]	[2.24]	[2.76]
β^{MKT}	1.27	1.32	1.22
	[10.74]	[9.84]	[16.77]
Two Factor Model (Market + Trade)			
α(%)	-0.01	0.17	0.18
	[-0.02]	[0.49]	[0.75]
β^{MKT}	1.29	1.34	1.24
	[13.60]	[12.32]	[20.98]
β^{T}	0.96	1.08	0.9
	[5.57]	[5.40]	[8.81]