Liberation Day or Market Loss? Evidence from Trump's 2025 Tariff Shock

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Abstract

We examine equity market responses to President Trump's April 2025 universal tariff announcement using event study methodology on S&P 500 constituents. Markets immediately registered substantial negative responses, with cumulative abnormal returns of -2.63% and 91% of firms experiencing declines over the $[-3, 3]$ event window. This reflects expectations of reduced future profitability. Cross-sectional analysis shows that firms in industries with higher import intensity experienced relatively smaller valuation declines, especially when they were more profitable and less financially constrained. Results are robust to alternative specifications using export intensity. Systematic comparison with March 2018 targeted tariffs demonstrates fundamental policy differences. Targeted measures created offsetting winners and losers while universal tariffs generated near-universal losses as comprehensive cost increases eliminated relative advantages. Results persist across multiple event windows and alternative specifications. Results challenge political rhetoric framing universal tariffs as stronger protection, showing markets recognize widespread negative valuation effects.

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1 Introduction

On April 2, 2025, U.S. President Donald Trump declared a "national emergency" arising from persistent trade deficits and announced a 10% baseline tariff on all imports with elevated duties reaching 145% on China. Financial markets responded immediately and provided real-time assessment of the policy's economic implications. This response offers crucial evidence for understanding how markets differentiate between universal and targeted trade barriers. Universal baseline tariffs differ fundamentally from targeted measures by altering competitive dynamics for all internationally engaged firms rather than specific sectors. The disconnect between political rhetoric promising prosperity and negative market valuations makes understanding these perceptions essential for policy evaluation.

We examine how financial markets assess universal vs targeted trade barriers by analyzing equity responses to President Trump's April 2025 announcement of comprehensive baseline tariffs on all imports. We focus our primary analysis on this initial announcement because it captures the market's first assessment of universal tariff policy before information dissemination and adaptation reduce subsequent announcement effects. This approach parallels our comparative analysis of targeted tariff announcement in March 2018, where we similarly examine initial market reactions to isolate genuine policy surprises from anticipated adjustments.

We provide the first firm-level analysis with cross-sectional heterogeneity and systematic 2018 comparison with 2025 universal tariff effects in modern financial markets. Existing research examines targeted measures and documents uneven sectoral effects with clear winners and losers (Amiti et al., 2021; Huang et al., 2023). Egger and Zhu (2020) demonstrate that U.S. tariffs imposed in 2018-19 during Trump's first term hurt domestic firms more severely than foreign competitors. Wengerek et al. (2025) find heterogeneous sectoral effects during 2018-19 tariff announcements, with China-exposed firms experiencing larger declines. However, comprehensive baseline tariffs remain unexplored despite their distinct theoretical implications. Standard trade theory predicts that universal tariffs impose economy-wide costs without offsetting competitive advantages. This contrasts with targeted measures that redistribute welfare across sectors (Krugman, 1991). Our contribution extends this literature by providing the first firm-level analysis of universal tariff effects with comprehensive cross-sectional heterogeneity and systematic comparison to targeted tariffs. Concurrent work by Siriopoulos et al. (2025) examines macroeconomic frameworks, while our focus on firm characteristics, mechanisms, and the targeted-universal distinction provides complementary microeconomic evidence on differential policy transmission.

Our empirical analysis proceeds in four stages. First, we examine aggregate market reactions to 2025 universal tariff announcement using standard event study methodology on all S&P 500 constituents. We calculate average abnormal returns (AARs) over multiple event windows to assess both immediate responses and persistence through extended periods. Second, we decompose these aggregate effects by industry sector to identify which segments of the economy bore the heaviest burden. Third, we investigate cross-sectional heterogeneity in firm responses through portfolio sorts and multivariate regressions. We examine how import intensity, firm size, and financial constraints shape vulnerability to universal tariffs. We test specific mechanisms through interaction terms, asking whether more profitable firms are better able to absorb or pass through costs and whether financially constrained firms suffer disproportionately. We confirm robustness using export intensity as an alternative trade exposure measure, finding similar patterns where export-oriented firms outperform domestic-focused firms. Fourth, we provide systematic comparison with the 2018 targeted China tariff announcement using identical methodology to distinguish universal policy effects from general trade barrier responses. This comparative framework allows us to assess whether universal and targeted tariffs generate fundamentally different market reactions or simply differ in magnitude.

Our analysis reveals three principal findings. First, markets immediately recognized universal tariffs as value-destroying, with equity valuation losses of $183.55 billion over the [0,2] event window.[1] The breadth of negative reactions, 91% of firms had negative cumulative abnormal returns (CARs), exceeds the mixed responses documented under targeted tariffs, where roughly half of firms experienced positive returns. This pattern suggests that universal policies eliminate competitive advantages for import-intensive firms while imposing widespread adjustment costs that reduce expected future cash flows.

Second, cross-sectional heterogeneity reveals that firms in industries with higher

[1] We note that stock price movements reflect shareholder wealth effects and expected firm profitability, not aggregate social welfare, which would require accounting for consumer surplus, tariff revenues, and distributional effects across stakeholders.

import intensity experienced relatively smaller valuation declines. We interpret this pattern cautiously because import intensity is measured at the industry level and may be correlated with other firm characteristics, including sector composition, profitability, cash holdings, and global integration. The interaction results suggest that this relative resilience is concentrated among more profitable and less financially constrained firms, consistent with differential adjustment capacity rather than tariff immunity.

Third, systematic comparison with "March 2018 targeted China tariffs" illuminates fundamental policy differences. The 2018 announcement produced mixed cross-sectional reactions: energy and utilities gained 3.07% and 3.26% CARs respectively as defensive sectors benefited from anticipated domestic demand shifts. In contrast, the 2025 universal tariffs generated near-universal losses, with energy, previously a winner, suffering the largest decline of CAR at -10.45%. This reversal occurs because universal tariffs eliminate relative competitive advantages while imposing input cost increases across all sectors simultaneously.

These findings advance understanding of trade policy effects through financial markets. Methodologically, we demonstrate that moving beyond aggregate market reactions to examine cross-sectional heterogeneity transforms descriptive event studies into mechanistic research. Theoretically, we provide empirical support for modern trade models emphasizing firm heterogeneity in adjustment capacity and competitive positioning (Melitz, 2003). Policy implications challenge political narratives framing tariffs as protecting domestic prosperity. Markets immediately price in anticipated cash flow reductions, supply chain disruptions, and retaliatory risks that political rhetoric often overlooks.

The paper proceeds as follows. Section 2 reviews literature on trade policy effects and develops testable hypotheses. Section 3 describes data and methodology. Section 4 presents results, beginning with aggregate market responses before examining cross-sectional variation through import intensity, firm size, financial constraints, and sectoral exposure. Section 5 provides systematic comparison with 2018 targeted tariffs to illuminate differential policy effects. Section 6 concludes with policy implications.

2 Theoretical framework and related literature

Trade policy effects on financial markets operate through multiple channels that existing literature has examined extensively, though primarily focusing on targeted measures rather than universal policies. We organize our review around three themes: market efficiency in policy evaluation, firm-level heterogeneity in trade exposure, and the political economy of protection.

2.1 Market-based policy evaluation

The efficient market hypothesis provides theoretical foundation for using stock returns to evaluate policy announcements (Fama, 1970). If markets efficiently aggregate information, stock price reactions reflect rational assessment of policy implications for future cash flows and discount rates. Event study methodology successfully documents market responses to policy interventions, from monetary announcements to regulatory changes (Bernanke, 1990; Campbell and Shiller, 1988; MacKinlay, 1997; Bernanke and Kuttner, 2005). Campbell and Shiller (1988) demonstrate how asset prices decompose into cash flow expectations and discount rate changes, grounding the use of stock returns for policy evaluation. Recent applications demonstrate that policy uncertainty generates substantial market effects, with trade policy uncertainty proving particularly consequential for firm valuations (Handley and Limaõ, 2017). Applying this framework to trade policy, Amiti et al. (2021) demonstrate that tariff announcements during 2018-19 generated significant stock price movements, with markets immediately incorporating implications rather than exhibiting delayed adjustment. Huang et al. (2023) extend this work internationally, finding negative spillovers to global equity markets as investors reassessed supply chain vulnerabilities.

However, existing research focuses exclusively on targeted tariffs. Universal baseline tariffs present distinct challenges for market evaluation, potentially generating coordinated expectations about economy-wide costs that amplify reactions beyond firm-level exposure predictions. Besides, Greenland et al. (2024) validate using equity reactions to infer trade exposure, showing markets aggregate supply chain information unavailable in customs data. Our comparative framework extends this methodology by demonstrating that universal and targeted tariffs generate qualitatively different cross-sectional patterns, not merely different magnitudes. This distinction reveals how policy scope, rather than firm exposure alone, determines whether trade barriers create winners and losers or impose systemic losses. If markets efficiently evaluate policy implications, we therefore expect that *universal tariff announcements will generate predominantly negative market reactions that exceed responses to targeted measures in both magnitude and breadth*. This follows from theoretical predictions that comprehensive policies impose economy-wide adjustment costs without creating offsetting competitive advantages that targeted measures provide to protected sectors.

2.2 Firm heterogeneity in trade exposure

Modern trade theory emphasizes heterogeneous firm responses to trade shocks based on productivity, size, and international engagement (Melitz, 2003). Extensive evidence documents that reducing input tariffs increases firm productivity substantially (Amiti and Konings, 2007; Topalova and Khandelwal, 2011). These findings suggest trade policy effects operate primarily through firm-level productivity channels. Egger and Zhu (2020) extend this to tariff increases, showing U.S. tariffs imposed during Trump's first term hurt domestic firms more than foreign competitors through disrupted supply chains.

Import intensity emerges as crucial for tariff exposure. High-import firms may possess superior profitability and stronger balance sheets that facilitate cost absorption (Amiti et al., 2019), while financial constraints reduce firms' adjustment capacity through supplier switching or inventory management (Manova, 2013). Recent work confirms adjustment mechanisms matter, with complete tariff pass-through at borders but heterogeneous retail pass-through depending on market power (Cavallo et al., 2021). These insights suggest the relationship between import intensity and stock returns depends critically on firm financial capacity. Import-intensive firms with strong financial positions are expected to outperform through adjustment flexibility, enabling them to reconfigure supply chains or absorb temporary cost increases. In contrast, financially constrained high-import firms should underperform due to limited adjustment capacity. This reconciles apparently contradictory predictions that rising input costs harm import-dependent firms, but superior financial characteristics enable cost absorption.

Firm size also affects trade shock adjustment. Larger firms maintain diversified supplier networks, command better financing terms, and possess greater bargaining power (Beck et al., 2005). We therefore expect smaller firms will experience more negative returns than larger firms when universal tariffs are announced, reflecting their limited diversification and restricted access to capital for supply chain adjustment.

2.3 Political economy of protection

Political economy literature emphasizes that protectionist policies reflect interest group pressures rather than aggregate welfare maximization (Grossman and Helpman, 1994).

Concentrated benefits to specific industries outweigh diffuse costs borne broadly across consumers and downstream producers. This creates persistent disconnect between political narratives promising prosperity and economic reality imposing net expected profitability declines. Fajgelbaum et al. (2020) estimate that 2018-19 tariffs generated loss to consumers and benefit to politically connected industries. The political economy of Trump's trade policies has generated substantial research. Wagner et al. (2018) document that stock prices of firms with greater Trump exposure rose following his 2016 election victory, reflecting anticipated regulatory rollbacks and tax cuts. Child et al. (2021) similarly find firms with Trump connections experienced positive abnormal returns. However, these gains proved temporary as tariff policies materialized. Blanchard et al. (2024) document that counties receiving greater tariff protection voted more heavily for Republicans in 2018, suggesting political benefits despite economic costs. More recent work by Cosma et al. (2025) and Ferriani et al. (2025) examines market reactions to Trump's 2024 re-election. They find sector-specific effects, with energy and financials gaining while environmentally-focused firms declined. This research highlights the distinction between election-related policy expectations and actual trade policy implementation effects.

While targeted tariffs induce idiosyncratic effects through strategic rent-seeking, universal tariffs impose systemic cost shocks. Building on equity-based inference methodologies of Greenland et al. (2024), we expect that sectoral responses to universal versus targeted tariffs will exhibit fundamental differences. Specifically, universal tariffs should eliminate the winners-and-losers dynamic of targeted protection, instead precipitating widespread negative abnormal returns as markets capitalize the aggregate rise in input costs.

3 Data and methodology

3.1 Sample construction

We examine all S&P 500 constituents as of April 2, 2025, when President Trump announced comprehensive tariff measures during a White House address. The announcement occurred after market close (4:30 PM EST), establishing April 3, 2025 as the first trading day incorporating this information. We collect daily stock prices and market capitalization data from LSEG Workspace for 503 firms. We also obtain firm-level financial characteristics including total assets, total debt, cash and equivalents, and net income from LSEG Workspace for fiscal year 2024, the most recent annual data available prior to the announcement. After dropping firms without sufficient return history or missing trading days during critical windows, we retain 500 firms for analysis.[2]

For comparative analysis examining targeted vs universal tariff effects, we construct an equivalent sample surrounding the March 23, 2018 announcement of 25% tariffs on $50 billion of Chinese imports. This represented the first major bilateral tariff action during Trump's first administration. For both periods, we apply identical filters: we exclude firms with insufficient return history or missing data during the estimation windows. The final dataset consists of 500 firms for the 2025 universal event and 475 firms for the 2018 targeted event.[3]

3.2 Empirical framework

3.2.1 Event study methodology

Following Brown and Warner (1985); MacKinlay (1997), we employ the market model to calculate the expected returns for each stock i as follows:

$$R_{i,t} = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} + \epsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ represents the logarithmic daily returns of stock i on day t, $R_{m,t}$ denotes the market return on the same day, and $\epsilon_{i,t}$ captures firm-specific shocks. We proxy the market return using the S&P 500 index. We estimate parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ using OLS regression over 250-day estimation period ending 10 days before the event window.[4] After deriving the parameters from the above model, we estimate the abnormal return (AR) as:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t}), \tag{2}$$

where $AR_{i,t}$ denotes the daily abnormal return for firm i on day t. We compute cumulative abnormal return (CAR) by summing daily abnormal returns over our chosen event windows.

To evaluate the statistical significance of both AR and CAR, following Ahmed et al. (2025), we implement the standardized cross-sectional test of Boehmer et al. (1991) (hereafter BMP) that adjusts for event-induced volatility by standardizing abnormal

[2] The S&P 500 index represents nearly 85% of the total market capitalization of U.S. stocks. The sample represents a broad cross-section of U.S. public firms across various industries.

[3] The slight difference in sample size reflects index composition changes between periods.

[4] This estimation period (days −260 through −11) provides sufficient observations for precise parameter estimates while avoiding contamination from information leakage as political discussions often precede formal announcements.

returns using forecast errors from the estimation period. We complement parametric tests with the non-parametric Wilcoxon signed-rank (hereafter WRank) test of the median ARs and CARs (Corrado and Zivney, 1992). The combination of parametric and non-parametric approaches strengthens inference, particularly given potential non-normalities in return distributions during periods of elevated policy uncertainty (Kolari and Pynnonen, 2011).

While President Trump's protectionist stance was well established, the relevant surprise on April 2, 2025 concerned the timing, scope, and especially the magnitude of the announced tariff schedule. Protectionist policy itself was anticipated, but the comprehensive 10% baseline tariff combined with elevated country-specific duties exceeded many market expectations. We verified that no other major economic policy announcements occurred on April 2, 2025, supporting our attribution of observed price movements to the tariff announcement. We acknowledge that our estimates may partially capture broader market reactions to policy uncertainty and macroeconomic implications rather than isolated tariff effects. To address potential anticipatory trading in the days preceding the announcement, we examine multiple event windows including a tighter window that isolates the immediate market response.

To ensure our results are not driven by omitted risk factors, we also use a market-adjusted abnormal return by including the Fama-French five-factors (Fama and French, 2015). The Fama-French five-factor model is based on SMB (size), HML (value), RMW (profitability), CMA (investment), and the overall market factor ($R_{m,t} - R_{f,t}$).[5]

3.2.2 Cross-sectional analysis

While aggregate market reactions provide initial evidence on tariff announcement effects, cross-sectional analysis allows us to test the specific channels through which universal tariffs affect firm value. We examine heterogeneity along two dimensions motivated by our theoretical framework. First, trade exposure measures capture direct vulnerability to tariff-induced cost increases and demand shifts. Second, firm characteristics measure adjustment capacity, determining whether firms can absorb shocks through profitability-related adjustment capacity and/or financial flexibility. The interaction between exposure

[5] Data is downloaded from Prof. Kenneth French's data library: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

and capacity provides insights into why some import-intensive firms weather tariffs better than others.

Three complementary variables capture firms' international engagement. First, import intensity, following Amiti and Konings (2007), is calculated from Bureau of Economic Analysis (BEA) Input-Output tables as the ratio of imported intermediate inputs to total intermediate inputs for each industry sector.[6] We assign industry-level values to firms based on primary GICS classification. This measure captures technological requirements for imported inputs following the effective rate of protection framework (Corden, 1966; Jones, 1975).[7] Recent research demonstrates imported inputs' crucial role in productivity. Firms, importing intermediate inputs, experience productivity gains ranging from 0.5% to 2.3% per percentage point reduction in input tariffs depending on country context (Amiti and Konings, 2007; Topalova and Khandelwal, 2011; Brandt et al., 2017). These productivity channels suggest import-intensive firms face complex tradeoffs under tariffs: rising costs vs potential competitive advantages if import dependence signals superior technology or financial strength. Second, export intensity, using geographic segment data from LSEG Workspace, is calculated as foreign revenue divided by total sales. This firm-specific measure reflects international revenue exposure from companies' 10-K geographic disclosures aggregated by LSEG Workspace. Third, supply chain complexity, constructed following Antràs and Chor (2013), is an index from 1 to 5 combining three BEA Input-Output dimensions: number of distinct intermediate input categories, import intensity of those inputs, and Herfindahl concentration of purchases. Industries with numerous specialized global inputs (semiconductors, aerospace) score higher than those with simple domestic chains (utilities, real estate).

After constructing trade exposure variables mentioned above, we construct a composite financial constraint index following Hadlock and Pierce (2010) as follows:[8]

$$FC_i = z(Leverage_i) - z(CashRatio_i) - z(ROA_i) - z(LogAssets_i), \tag{3}$$

where $Leverage_i$ denotes total debt divided by total assets, $CashRatio_i$ denotes cash

[6] The BEA Use Tables decompose purchases into domestic and imported components at detailed industry levels. Data is downloaded from https://apps.bea.gov/iTable/?reqid=1602&isuri=1&step=8&categories=Core

[7] Our import intensity measure provides comprehensive coverage but introduces measurement error by assigning industry values to all firms within sectors. This approach follows standard practice (Amiti and Konings, 2007).

[8] They demonstrate that simpler measures outperform complex constraint indices.

and equivalents divided by total assets, ROA_i is net income divided by total assets, and $LogAssets_i$ represents log total assets capturing firm size. All components are standardized to zero mean and unit variance. Higher values indicate greater constraints from high leverage (limited debt capacity), low cash (inability to self-finance), weak profitability (reduced creditworthiness), and small size (restricted market access).

After constructing the financial constraints index, we employ two complementary approaches: portfolio analysis and multivariate regressions. Portfolio sorts into terciles by market capitalization, import intensity, and financial constraints provide non-parametric evidence on univariate relationships. For size-based analysis, we report both daily average abnormal return (AAR) and cumulative abnormal return (CAR) over event windows. For import intensity and financial constraint sorts, we report mean CAR over event windows. All portfolio returns are calculated as equal-weighted averages, giving each firm equal weight regardless of market capitalization. Results are tested using BMP and WRank statistics, which evaluate whether observed abnormal returns differ significantly from zero. Two-way independent sorts combining size and import terciles create nine portfolios that examine whether exposure effects vary with firm scale. This non-parametric approach imposes no functional form assumptions while revealing basic patterns.

Multivariate regressions then control for multiple characteristics simultaneously. The baseline specification regresses CAR on trade exposure and firm characteristics:

$$CAR_i = \alpha + \beta_1 ImportIntensity_i + \beta_2 LogAssets_i + \beta_3 CashRatio_i + \beta_4 Leverage_i + \epsilon_i \tag{4}$$

To test our mechanism hypotheses, we estimate augmented specifications including interaction terms. For profitability-related adjustment capacity, we interact import intensity with a dummy for high profitability (ROA > 10%). The coefficient on this interaction tests whether more profitable firms mitigate import exposure more effectively, whether through partial cost pass-through, cost management, or supply-chain adjustment. Similarly, for financial constraints, we interact import intensity with our composite constraints index to assess if constrained firms suffer disproportionately. We report heteroskedasticity-robust standard errors for all specifications.

3.2.3 Comparative analysis: universal vs targeted tariffs

To formally test whether universal tariffs generate distinct market reactions compared to targeted measures, we employ a comparative event study framework estimating Equations (1) and (2) separately for 2018 and 2025 samples. We also estimate the cross-sectional regression specified in Equation (4) separately for both samples. This approach allows us to determine if the pricing of trade risk has fundamentally shifted from a "winners and losers" dynamic (2018) to a "systemic cost shock" (2025). Three comparison dimensions reveal these patterns. Aggregate reactions show overall expected profitability assessment differences. Sectoral decomposition demonstrates how protection patterns shape cross-sectional effects. Firm-level analysis tests whether the same characteristics predict vulnerability across policy types, or whether universal measures generate qualitatively different exposure patterns.

4 Empirical results

4.1 Aggregate market response

We begin by documenting the breadth and magnitude of market reaction to universal tariffs. Table 1 presents descriptive statistics of cumulative abnormal returns across eleven event windows designed to capture pre-announcement periods, the announcement window itself, and post-announcement periods. The results show that markets immediately recognized universal tariffs as fundamentally value-destroying. Mean CAR reached −2.7% over [−3,3], with 91% of firms experiencing negative returns during this window. Post-announcement consistency proved remarkable. 82% of firms declined during [0,2] and 91% during [0,3], indicating markets did not reverse initial assessments.

Insert Table 1 approximately here

Three temporal patterns emerge. First, pre-announcement windows show limited aggregate drift. Only 27% of firms declined during [−3,0], and the mean CAR over that window was 0.5%, indicating no broad market-wide selloff before the announcement. At the same time, the absence of aggregate drift does not rule out partial anticipation in particular cross-sections, especially among trade-exposed firms. We therefore place greater emphasis on the tighter [−1,1] window and the immediate post-announcement windows when interpreting the market's response to the policy shock. Second, post-announcement negativity intensified: the proportion of declining firms rose from 73% during [0,1] to 91% during [0,3]. This suggests that markets incorporated additional negative information as they evaluated supply chain implications. Third, consistency across windows reveals coherent valuation reassessment rather than random responses.

Table 2 reports how this reassessment unfolded day by day. Panel A presents daily average abnormal returns (AARs) for the overall market across seven event days centered on the announcement. Day 0 exhibited positive AAR of 0.41% ($p < 0.01$) because the announcement occurred after market close at 4:30 PM EST, meaning Day 0 captures pre-announcement trading rather than policy response. Markets processed the announcement overnight, with Days +1 through +3 delivering -3.16% (-1.31%, -1.31%, and -0.54%) cumulative decline as investors evaluated actual implications. This delayed negative reaction is consistent with complex policy announcements requiring detailed analysis to assess supply chain disruptions and competitive dynamics. Panel B confirms these patterns through cumulative abnormal returns (CARs), with [0,3] window showing -2.75% CAR, reinforcing that markets reacted negatively once they processed the announcement's implications.

Insert Table 2 approximately here

The magnitude substantially exceeds documented responses to targeted tariff measures. While the 2018-2019 trade war eroded U.S. firm valuations by approximately 6.7% cumulatively (Amiti et al., 2021), the cross-sectional response was decidedly mixed, characterized by heterogeneous sectoral effects and offsetting winners (Wengerek et al., 2025). In sharp contrast, the universal nature of the 2025 announcement precipitated a 91% negative reaction rate, effectively eliminating the winners-and-losers pattern associated with targeted protectionism. This systemic repricing aligns with Greenland et al. (2024), confirming that equity markets rapidly aggregate complex supply chain exposures, such as the elimination of comparative advantages, that traditional trade data fail to capture. This aggregate negativity raises a natural question: which sectors did markets expect to suffer most severely, and did any industries escape the broad-based decline?

4.2 Sectoral heterogeneity

To understand the heterogeneity masked by aggregate statistics, we decompose market response by industry. Table 3 reports industry-specific daily AARs for eleven GICS sectors across seven event days. Three distinct sectoral patterns emerge. First, globally integrated sectors suffered severe losses concentrated immediately post-announcement. Energy experienced catastrophic declines primarily on Days +1 and +2 with AAR of −6.24% and −6.15% respectively, indicating rapid negative reassessment once markets processed implications for refinery input costs. Materials showed steady deterioration with Day +2 AAR of −2.26%, while financials declined −2.12% and −2.70% on Days +1 and +2 respectively. These reflect expectations of reduced lending activity and cross-border disruption.

Insert Table 3 approximately here

Second, defensive sectors showed initial resilience that evaporated as markets traced indirect vulnerabilities. Consumer staples exhibited AAR of 0.85% on Day +1, apparently reflecting expectations of stable domestic demand. However, Day +2 brought sharp reversal with AAR of −2.93% as investors recognized imported ingredient and packaging exposure. Utilities similarly rose 0.39% on Day +1 as seemingly insulated non-tradable services, but Days +2 and +3 delivered declines of −3.86% and −1.43% when capital equipment and fuel cost implications emerged. Third, information technology uniquely maintained strength throughout the event window, with Day +3 brought positive AAR of 1.71% ($t = 4.04$). This reflects superior financial characteristics and service-based revenue models that reduce physical goods tariff exposure.

Table 4 cumulates these daily patterns across multiple event windows. Energy's CAR of −10.45% over [−3,3] represents the most severe sectoral decline, with losses persisting across all window specifications. Materials (−4.78%) and financials (−4.87%) suffered substantial aggregate losses over [−3,3], while defensive sectors showed complete reversal from initial strength. Consumer staples evolved from 0.83% during [−1,1] to −2.24% during [0,2], quantifying the swing as indirect vulnerabilities emerged. Information technology's exceptional performance appears clearly in cumulative terms with CAR of 2.09% over [−3,3].

Insert Table 4 approximately here

The severe negative response of the energy sector (-10.45% CAR over [−3,3]) merits brief discussion, as the United States is largely energy independent. This pattern likely reflects broader macroeconomic channels rather than direct import exposure. Energy sector valuations are sensitive to aggregate demand expectations, and recession concerns triggered by comprehensive tariffs would reduce fuel consumption. Additionally, the tariff announcements coincided with rising US Treasury yields, increasing borrowing costs for capital-intensive energy firms. More generally, our estimated effects capture multiple transmission channels beyond direct tariff-induced input costs, including anticipated demand contraction, tightening credit conditions, and heightened policy uncertainty.

Appendix Table A.1 provides insight into this resilience: technology firms possess superior profitability (mean ROA 12% vs 8% market average), substantial cash reserves (mean cash ratio 19% vs 10% market average), and service-based revenues reducing physical goods tariff exposure. Appendix Table A.2 reports these sectoral patterns across all eleven event windows and confirms that the relative sectoral rankings remain stable across every window specification. These represent robust patterns rather than artifacts of particular window choices.

Beyond percentage returns, Table 5 reports aggregate valuation changes by sector using market capitalizations from April 1, 2025, the trading day before the announcement. Over the [0,2] window, the net aggregate valuation change across the sample is approximately −183.55 billion USD. Financials recorded the largest absolute decline at −305.87 billion USD, followed by Energy at −210.29 billion USD. Only Information Technology and Consumer Discretionary generated positive aggregate valuation changes, at 459.12 billion USD and 236.90 billion USD, respectively. These gains partially offset the broader losses across the remaining sectors, but they did not fully offset the $927.71 billion in aggregate declines across nine declining sectors.

Insert Table 5 approximately here

The consistency of sectors' aggregate valuation rankings strengthens confidence in these patterns. Energy remained worst-performing across all specifications, while technology maintained relative strength. However, sectoral patterns alone cannot fully explain cross-sectional variation. Within each sector, firms differ substantially in size, financial position, and international exposure, necessitating examination of firm-level characteristics. We start by analyzing size effects.

4.3 Transmission mechanisms and broader market effects

The sectoral patterns documented above reveal that equity market responses to universal tariffs operate through multiple transmission channels beyond direct import cost increases. Three complementary mechanisms explain the breadth and magnitude of observed valuation effects. First, direct tariff cost channels impose immediate input price increases for import-dependent firms. Universal baseline tariffs eliminate sourcing substitution possibilities that targeted measures permit, forcing firms to absorb strictly inferior cost structures. This channel explains why even domestically-oriented sectors experienced negative returns as intermediate input costs rose across supply chains.

Second, markets priced in aggregate demand contraction expectations triggered by tariff-induced inflation and purchasing power erosion. The severe energy sector decline exemplifies this mechanism. Despite substantial U.S. energy independence limiting direct import exposure, energy valuations are highly sensitive to aggregate demand expectations. Comprehensive tariffs signal recession risk through multiple paths including reduced consumer spending, business investment delays, and supply chain disruptions. Markets incorporated these demand-side effects into valuations alongside direct cost channels. Third, financial tightening through bond market reactions amplified initial tariff effects. U.S. Treasury yields rose sharply in days following the announcement as investors reassessed fiscal sustainability and inflation risks. Higher borrowing costs particularly burdened leveraged firms and capital-intensive sectors, explaining why financially constrained firms experienced disproportionately negative returns regardless of import exposure. This financial channel operated independently of trade exposure but magnified tariff policy effects through general equilibrium adjustments.

Fourth, policy uncertainty amplification created option value effects beyond static cost calculations. Universal tariff announcements generated uncertainty regarding implementation details, sectoral exemptions, and retaliatory responses from trading partners. Firms facing irreversible investment decisions rationally delayed commitments pending clarity, reducing expected investment flows and depressing valuations. This uncertainty channel persisted beyond the immediate announcement window as markets awaited policy clarification. These mechanisms operated simultaneously and interactively. The $[-3,3]$ window captures their combined effect as markets processed direct cost implications, updated macroeconomic forecasts, incorporated financial market spillovers, and priced policy uncertainty.[9]

4.4 Firm size effects

Theory predicts smaller firms face greater adjustment challenges through multiple channels: less diversified supplier networks limiting rapid sourcing switches, weaker bargaining power, more binding financial constraints restricting access to capital, and limited compliance capacity for navigating complex tariff schedules. To test these predictions, we partition the sample into size terciles based on market capitalization. Table 6 reports both daily AARs (Panel A) and CARs (Panel B) across multiple event windows.

Insert Table 6 approximately here

The evidence confirms size-based vulnerability. Panel A reveals that on Day +1, AARs were −2.09% for small firms and −0.50% for large firms. The gap between small and large firms widens over longer windows as markets incorporated information about differential adjustment capacity. Panel B shows small firms declined −3.12% over [−3,3] compared to −1.80% for large firms, representing a −1.32 percentage point differential that proves statistically and economically significant.

Economic magnitude proves substantial beyond statistical significance. Small firms' aggregate market capitalization declined approximately \$820.12 billion during [−3,3] relative to expected performance, while large firms lost \$679.71 billion despite having far greater aggregate value.[10] This indicates proportionally larger impact on small firm shareholders: a 3.1% loss of total value for small firms versus 1.8% for large firms. Appendix Table A.3 presents expanded analysis over additional event windows, confirming the robustness of size effects. Having established that small firms suffered disproportionately, we now examine a more subtle question: how does trade exposure itself affect firm value, and does the relationship depend on firm characteristics?

4.5 Import intensity and financial constraints

Conventional wisdom offers clear prediction that firms importing substantial intermediates should underperform during tariff announcements as rising input costs directly reduce

[9] Extended negative returns through Day +9 (Appendix Table A.10 and Table A.11) confirm markets interpreted tariffs as permanent structural shifts rather than temporary policy noise, consistent with the transmission mechanisms outlined above operating through fundamental cash flow expectations rather than transitory discount rate fluctuations.

[10] These values are calculated by multiplying the mean CAR for each size tercile by the corresponding aggregate market capitalization. Dollar values are reported in USD billions.

profitability. To test this hypothesis, we construct portfolios sorted by import intensity measured at the industry level. Table 7 presents results that show interesting patterns.

Insert Table 7 approximately here

Panel A reports tercile portfolio sorts. Firms in the high-import tercile recorded a mean CAR of 0.4% over [−3,3], compared with −4.8% for firms in the low-import tercile, a 5.2 percentage point spread. We interpret this pattern cautiously. Because import intensity is assigned at the industry level from BEA input-output tables, this result should not be read as evidence that greater firm-level import dependence benefits from tariffs. Rather, it indicates that firms in higher-import industries experienced relatively smaller valuation declines during this episode, potentially because the import-intensity measure is correlated with other characteristics such as sector composition, profitability, cash holdings, and global integration. Consistent with this interpretation, import intensity is positively correlated with ROA (0.271) and cash holdings (0.219) in Appendix Table A.4. The result therefore points to cross-sectional heterogeneity in adjustment capacity, not tariff immunity.

This counterintuitive pattern warrants further investigation rather than strong structural interpretation. We therefore examine two candidate channels. First, more profitable firms may be better able to absorb or partially pass through cost increases. Second, financially flexible firms may be better positioned to reconfigure supply chains or absorb temporary shocks. The interaction results below should therefore be interpreted as evidence consistent with these channels, not as definitive identification of them.

The literature on tariff pass-through establishes that cost incidence is not uniform, but conditional on market power and operational flexibility (Flaaen et al., 2020; Cavallo et al., 2021). Consistent with heterogeneous adjustment capacity, our univariate analysis shows that firms in higher-import industries experienced relatively smaller valuation declines. Because import intensity is measured at the industry level, we do not interpret this pattern as direct evidence of firm-level resilience. We therefore examine whether the interaction results are consistent with investors differentiating firms by their ability to absorb or adapt to tariff-related cost shocks.

Table 8 formally tests the transmission mechanisms through interaction specifications.[11] Panel A establishes baseline relationships before examining interaction effects. Specification (1) demonstrates that financially constrained firms exhibit significantly more negative returns (coefficient: -0.022 over $[-3,3]$, t=-3.53), confirming constrained firms face greater adjustment difficulties. Specification (2) shows profitable firms generate significantly more positive returns (coefficient: 0.025 over $[-3,3]$, t=3.67), consistent with superior shock absorption capacity. Specifications (3) and (4) include both import intensity and firm characteristics additively without interaction terms. Import intensity remains robustly positive, financial constraints remain negative, and high profitability remains positive when entered together, demonstrating that each variable maintains its expected sign and economic significance.

Insert Table 8 approximately here

Panel B tests the profitability-related adjustment-capacity channel by including an interaction between import intensity and a high profitability indicator (ROA exceeding 10%). While the baseline effect of import intensity is positive, the interaction with high profitability is economically dominant ($\beta = 0.460$, $t = 2.75$). This pattern suggests that the positive relationship between import exposure and returns is concentrated among firms with stronger profitability profiles, which may reflect greater margin buffers, cost management capacity, operational flexibility, or access to capital markets. We do not interpret ROA as a direct measure of markups or pure pricing power. Panel C tests the financial constraints hypothesis by interacting import intensity with our composite financial constraint index. The result reveals the limits of this resilience. The interaction between import intensity and financial constraints is significantly negative ($\beta = -0.188$), effectively neutralizing the positive baseline effect ($\beta = 0.211$) over $[-3,3]$ for constrained firms. This reversal indicates that operational flexibility is conditional on financial slack. Without access to capital, firms cannot rapidly reconfigure supply chains. This friction is economically substantial. As detailed in Appendix Table A.5, the "importer premium" (the return spread between high- and low-import firms) collapses from 6.8% among

[11] We use return on assets (ROA) as a proxy for firms' ability to absorb and pass through cost increases. While ROA is an imperfect measure that reflects multiple factors including cost efficiency, capital intensity, and financial structure rather than pure pricing power, it provides a readily available indicator of firms' profitability margins. Firms with higher profitability may have greater flexibility to manage input cost increases through either cost pass-through to customers or operational adjustments. We acknowledge this measure has limitations and interpret our results as reflecting general financial performance rather than pure market power.

unconstrained firms to just 1.2% among the most constrained. The differential of 5.6 percentage points between constraint terciles confirms that financial flexibility critically moderates how firms respond to import cost increases. These interaction results suggest that the relative outperformance of firms in higher-import industries is concentrated among firms with stronger profitability and financial flexibility. Given the coarse industry-level exposure measure, we interpret this pattern as consistent with heterogeneous adjustment capacity rather than as evidence that import intensity itself proxies for firm quality.

Table 9 presents comprehensive cross-sectional regressions that control simultaneously for multiple firm characteristics. Import intensity remains robustly positive across most specifications ($\beta = 0.211$ over $[-3,3]$ and 0.244 over $[0,2]$) after controlling for firm characteristics.[12] Notably, the cash ratio enters positively ($\beta = 0.111$), further validating the liquidity channel. Firm size enters negatively, suggesting that in the context of rapid policy shifts, operational agility outweighs pure scale.

Insert Table 9 approximately here

Robustness tests confirm that our core findings are not artifacts of sector composition or measurement choices. Appendix Table A.6 excludes energy and financial sectors sequentially to address concerns that these industries' unique characteristics drive results. The positive import premium persists after excluding energy and financial sectors, though the attenuation in magnitude suggests these industries amplify the effect. Negative pre-announcement coefficients for import-intensive firms are more consistent with partial anticipation or pre-positioning than with a perfectly clean surprise. For that reason, we interpret the wider windows cautiously and place greater weight on the tighter $[-1,1]$ and immediate post-announcement windows, where the market response is more plausibly tied to the policy announcement itself. Alternative specifications of financial constraints are presented in Appendix Table A.7. The results yield qualitatively identical interaction terms, verifying that the results are robust to the specific construction of the constraint index.

[12] The positive relationship between import intensity and returns is most pronounced in extended windows. In the tighter $[-1,1]$ window, the import-intensity coefficient is near zero and statistically insignificant, suggesting that this relationship is not robust in the narrowest specification. The negative coefficient in the pre-announcement $[-3,0]$ window (Table 8 Panel C and Appendix A.6) is more naturally interpreted as evidence of partial anticipation or pre-positioning ahead of the announcement rather than as evidence against anticipation. We therefore view the post-announcement windows as more informative for interpreting the immediate response to the tariff shock.

Appendix Table A.8 further decomposes the "importer premium" using two-way independent sorts by firm size and import intensity. The performance gap between high- and low-import firms increases with size, reaching 7.6% for large-cap firms but shrinking to 2.2% for small-cap firms. We interpret this gradient cautiously. Rather than implying that import intensity captures firm quality, the pattern is consistent with larger firms in higher-import industries having greater capacity to absorb tariff-related cost shocks.

We examine export intensity as an alternative measure of trade exposure. Appendix Table A.9 presents portfolio sorts, cross-sectional regressions, and interaction tests using export intensity calculated from 10-K disclosures. Panel A reveals that high export-intensity firms generated significantly less negative returns than low export-intensity firms. The tercile analysis shows high exporters experienced −0.3% returns compared to −4.5% for low exporters, a 4.2 percentage point differential. The quintile spread between Q5 and Q1 reaches 6.3 percentage points, paralleling our import intensity findings where high-import firms similarly outperformed.

Panel B confirms this relationship in multivariate regressions. Export intensity exhibits positive coefficients of 0.084 over [−3,3] (t=3.39) and 0.065 over [0,2] (t=3.29), both statistically significant at the 1% level. The effect becomes insignificant in the narrow [−1,1] window, consistent with import intensity patterns in Table 9. Panel C tests whether firm characteristics moderate export exposure. Export × High ROA shows positive coefficients in wider windows (0.144, t=2.46 over [−3,3]), though interaction significance varies across specifications. Export × FC Index exhibits negative coefficients (−0.072, t=−3.88 over [−3,3]), indicating financially constrained exporters experience worse outcomes, consistent with import intensity findings. The parallel between the import- and export-intensity results suggests that both measures may be correlated with broader dimensions of international engagement and adjustment capacity. We therefore interpret these patterns as reduced-form evidence of heterogeneous exposure and resilience, not as direct evidence that either measure captures firm quality.

4.6 Medium-term dynamics and robustness checks

To distinguish between behavioral overreaction and the rational discounting of structural economic damage, we extend our analysis through Day +9. Appendix Table A.10 reports daily AARs for Days +4 through +9 across all eleven GICS sectors, while Appendix

Table A.11 presents CARs over extended event windows. Medium-term analysis reveals 93% persistence of initial valuation effects through Day +9 (CAR [0,9] = -2.37% vs [0,2] = -2.21%), consistent with markets pricing permanent cash flow changes rather than temporary discount rate fluctuations. This is consistent with Campbell and Shiller (1988), who show that the lack of mean reversion suggests investors interpret universal tariffs as a permanent shock to future cash flows. This is distinct from the transient policy noise often documented in trade literature (Baker et al., 2026). While Day +5 exhibited a technical rebound (AAR of +1.33%), the sustained sectoral deficits, particularly in energy and defensive industries, align with models emphasizing the long-run productivity costs of autarkic distortions (Atkeson and Burstein, 2010; Perla et al., 2021).

We further confirm that these valuation effects are not driven by omitted systematic risk factors. Appendix Table A.12 reports aggregate and sector-specific daily AARs using the Fama-French five-factor model that controls simultaneously for market, size, value, profitability, and investment factors. Appendix Table A.13 presents CARs under this alternative specification. Although controlling for these factors moderates the aggregate [−3,3] CAR to −1.94% (vs. −2.63% in the market model shown in Table 2), the cross-sectional hierarchy remains qualitatively unchanged. The stability of coefficients across single- and multi-factor specifications reinforces our interpretation that the observed price discovery reflects genuine tariff-induced fundamental shifts rather than factor loading anomalies.

Having established the systemic valuation impact of universal tariffs, we turn to a fundamental policy counterfactual: do these patterns simply reflect generic trade aversion, or are they unique to the comprehensive scope of the 2025 policy? We next benchmark these findings against the 2018 targeted tariff episode to isolate the specific asset pricing implications of universal versus surgical protectionism.

5 Comparing universal and targeted tariffs

To contextualize the 2025 market responses, we conduct a descriptive comparison with the March 2018 announcement of targeted tariffs on China. We emphasize this comparison is descriptive rather than causal, as the episodes differ in tariff scope, macroeconomic conditions, and the degree of anticipation. The 2018 targeted tariffs followed sustained trade tensions, while the 2025 universal tariffs' specific magnitude contained greater surprise elements. With these caveats, the comparison nonetheless illuminates how market responses differed across policy regimes. While targeted tariffs generate winners and losers by shielding specific sectors while taxing others (Grossman and Helpman, 1994), universal tariffs impose symmetric cost shocks across the economy. We benchmark our 2025 findings against the March 23, 2018 announcement of targeted tariffs on $50 billion of Chinese imports.

5.1 Aggregate market responses

Table 10 presents the comparative event study results. The 2018 targeted tariffs produced essentially neutral aggregate response with CAR of -0.14% ($t = 0.87$) during $[-1,1]$. Over the extended $[-3,3]$ window, markets actually registered slight positive reaction of 0.38% ($t = 2.82$). These aggregate responses contrast dramatically with 2025's -1.07% during $[-1,1]$ and -2.63% over $[-3,3]$. More revealing than means, cross-sectional distributions differed fundamentally.

Insert Table 10 approximately here

The distributional data confirms a shift in the nature of the shock. Under the 2018 targeted regime, only 36% of firms experienced negative abnormal returns, consistent with a policy designed to reallocate rents. Under the 2025 universal regime, this proportion surged to 91%. This transition from heterogeneous incidence to systemic repricing demonstrates that universal tariffs eliminate the offsetting competitive advantages typically associated with protectionism, leaving only the anticipated cash flow reductions of higher input costs.

5.2 Sectoral reversal and supply chain rigidity

The sectoral decomposition in Table 10 provides the most direct evidence of this mechanism change.[13] We document a dramatic "reversal of fortune" for defensive sectors. Energy, which gained 3.07% during the 2018 targeted episode (presumably anticipating reduced import competition), suffered a precipitous 10.45% decline in 2025, a 13.5 percentage point swing. Similar reversals occurred in Utilities ($+3.26\% \rightarrow -2.23\%$) and Real Estate ($+3.13\% \rightarrow -3.72\%$).

These reversals support the theoretical predictions of Grossman et al. (2024), who argue that universal tariffs cause severe supply chain disruption by eliminating substitution

[13] Complete daily abnormal returns and extended window analysis for the March 2018 announcement appear in Appendix Tables A.13 and A.14, providing detailed temporal dynamics parallel to our 2025 analysis in Tables 3 and 4.

possibilities. Under targeted tariffs, firms can optimize by shifting sourcing to non-targeted partners. Universal tariffs remove this arbitrage opportunity, forcing firms to absorb strictly inferior input cost structures. Consequently, sectors that previously benefited from the "diversionary protection" of targeted tariffs find themselves fully exposed to the "cost-push" shock of universal measures. Conversely, the Information technology sector's relative improvement (-1.66% in 2018 to $+2.09\%$ in 2025) suggests that the intervening years of supply chain diversification effectively hedged these firms against renewed shocks.

5.3 Firm-level heterogeneity and interpretation of trade exposure

Beyond aggregate and sectoral patterns, we examine whether firm characteristics predict returns differently across policy types. The relationship between import intensity and firm value also inverts across regimes. Under the 2018 targeted tariffs, high-import firms underperformed by 2.1 percentage points, as they were the direct targets of the policy. Under the 2025 universal tariffs, high-import firms *outperformed* by 5.2 percentage points.[14] This reversal is informative but should be interpreted cautiously. In a targeted regime, import intensity is more closely related to direct bilateral exposure. In a universal regime, the same industry-level measure may instead proxy for broader differences in sectoral composition and firm characteristics. We therefore interpret the 2025 outperformance of high-import firms as evidence of heterogeneous adjustment capacity rather than evidence that greater import dependence itself is advantageous under universal tariffs. This suggests that when policy shocks are systemic, firms' ability to absorb or adapt to cost shocks may matter more for cross-sectional pricing than simple exposure measures alone.

5.4 Implications for political economy

Our results challenge the populist rhetoric that broad-based protectionism strengthens domestic industry. Instead, equity markets view universal tariffs as unambiguously value-destroying. The data suggests that the "efficient frontier" of trade policy, to the extent one exists, relies on the surgical precision of targeted measures to concentrate benefits on politically organized groups while dispersing costs (Grossman and Helpman, 1994). Universal tariffs violate this logic by imposing concentrated costs on everyone. The efficient

[14] Detailed results for all analyses for 2018 tariff announcement that are used for 2025 tariff announcement are available upon request.

policy response to legitimate security or labor concerns likely lies in targeted non-tariff interventions (e.g., subsidies or stockpiling) rather than blunt universal instruments that, as our evidence shows, evaporate equity value across the board.

6 Conclusion

This study leverages the efficiency of equity markets to evaluate the economic consequences of universal vs targeted trade policies. We document that the shift from surgical protectionism (2018) to comprehensive universal tariffs (2025) fundamentally alters the mechanism of negative valuation effects. While targeted measures generate a mixed distribution of winners and losers, universal tariffs precipitate a systemic contraction, erasing 2.63% of aggregate equity value and inducing negative abnormal returns in 91% of firms.

Our primary contribution lies in documenting that firms with stronger profitability and financial flexibility were better insulated during the universal tariff episode. High-import firms outperformed on average, but because import intensity is measured at the industry level, we interpret this as a reduced-form correlation consistent with heterogeneous adjustment capacity rather than direct evidence that import dependence was beneficial.

Methodologically, this paper demonstrates the utility of asset pricing as a real-time diagnostic for trade policy. The macro literature documents large impacts of trade on income and growth (Frankel and Romer, 1999; Alcalá and Ciccone, 2004; Feyrer, 2019; Wacziarg and Welch, 2008), though identifying causality remains challenging. Our financial market approach complements this work by providing real-time assessment of expected productivity changes through stock valuations, following recent methodological advances by Greenwald et al. (2025) and Atkeson et al. (2025) in decomposing stock returns into cash flow and discount rate components. By aggregating dispersed information regarding supply chain vulnerabilities, equity markets provide an immediate "shadow valuation" of productivity shocks that lags in traditional macroeconomic data. The market's verdict is clear. Universal tariffs are not merely an escalation of targeted measures, but a distinct policy class that severs the link between protection and competitive advantage, resulting in pure anticipated cash flow reductions.

Several limitations qualify our findings. Our estimates capture market expectations at announcement rather than realized outcomes, which depend on subsequent policy implementation and potential modifications. The universal tariff regime differs from historical trade policy changes, limiting our ability to compare with prior episodes beyond the 2018 targeted tariffs. Our industry-level import intensity measure, while grounded in BEA input-output tables, may not capture all firm-specific supply chain exposure. Finally, distinguishing between direct tariff effects and broader macroeconomic channels (recession fears, monetary policy expectations, policy uncertainty) remains challenging given the comprehensive scope of the announcement.

Our analysis suggests several productive avenues for future research. First, our focus on short-term equity reactions leaves open the question of long-run equilibrium outcomes where future work should track firm adaptation over multi-year horizons to assess whether initial valuations persist. Second, extending this framework to private firms, where the absence of public equity capital may exacerbate the financial constraints channel, would verify the universality of our mechanism. Finally, examining the cross-border spillovers of universal tariffs would clarify whether the negative valuation effects we document are a purely domestic phenomenon or a global repricing of trade risk.

Our analysis demonstrates that sophisticated investors distinguish sharply between political rhetoric and economic fundamentals. Despite promises that protectionism enhances prosperity, markets immediately recognize the widespread negative valuation effects inherent in universal tariffs. This disconnect suggests that while targeted measures may offer strategic utility, comprehensive barriers sever the link between protection and competitive advantage, imposing anticipated cash flow reductions that financial markets price in real-time.

References

Ahmed, S., Hasan, M., Hossain, A., and Saadi, S. (2025). The comeback effect: Market responses to Trump's 2024 election victory. *Economics Letters*, 247:112170. https://doi.org/10.1016/j.econlet.2025.112170.

Alcalá, F. and Ciccone, A. (2004). Trade and Productivity. *The Quarterly Journal of Economics*, 119(2):613–646. https://doi.org/10.1162/0033553041382139.

Amiti, M., Kong, S. H., and Weinstein, D. E. (2021). Trade Protection, Stock-Market Returns, and Welfare. NBER Working Paper 28758, National Bureau of Economic Research. https://doi.org/10.3386/w28758.

Amiti, M. and Konings, J. (2007). Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. *American Economic Review*, 97(5):1611–1638. https://doi.org/10.1257/aer.97.5.1611.

Amiti, M., Redding, S. J., and Weinstein, D. E. (2019). The Impact of the 2018 Tariffs on Prices and Welfare. *Journal of Economic Perspectives*, 33(4):187–210. https://doi.org/10.1257/jep.33.4.187.

Antràs, P. and Chor, D. (2013). Organizing the Global Value Chain. *Econometrica*, 81(6):2127–2204. https://doi.org/10.3982/ECTA10813.

Atkeson, A. and Burstein, A. T. (2010). Innovation, Firm Dynamics, and International Trade. *Journal of Political Economy*, 118(3):433–484. https://doi.org/10.1086/653690.

Atkeson, A., Heathcote, J., and Perri, F. (2025). The End of Privilege: A Reexamination of the Net Foreign Asset Position of the United States. *American Economic Review*, 115(7):2151–2206. https://doi.org/10.1257/aer.20230732.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636. https://doi.org/10.1093/qje/qjw024.

Baker, S. R., Bloom, N., Davis, S. J., and Kost, K. (2026). Policy news and stock market volatility. *Journal of Financial Economics*, 175:104187. https://doi.org/10.1016/j.jfineco.2025.104187.

Beck, T., Demirguc-Kunt, A., and Levine, R. (2005). SMEs, growth, and poverty: Cross-country evidence. *Journal of Economic Growth*, 10(3):199–229. https://doi.org/10.1007/s10887-005-3533-5.

Bernanke, B. S. (1990). The Federal Funds Rate and the Channels of Monetary Transnission. NBER Working Paper 3487, National Bureau of Economic Research. https://doi.org/10.3386/w3487.

Bernanke, B. S. and Kuttner, K. N. (2005). What Explains the Stock Market's Reaction to Federal Reserve Policy? *The Journal of Finance*, 60(3):1221–1257. https://doi.org/10.1111/j.1540-6261.2005.00760.x.

Blanchard, E. J., Bown, C. P., and Chor, D. (2024). Did Trump's trade war impact the 2018 election? *Journal of International Economics*, 148:103891. https://doi.org/10.1016/j.jinteco.2024.103891.

Boehmer, E., Masumeci, J., and Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics*, 30(2):253–272. https://doi.org/10.1016/0304-405X(91)90032-F.

Brandt, L., Van Biesebroeck, J., Wang, L., and Zhang, Y. (2017). WTO Accession and Performance of Chinese Manufacturing Firms. *American Economic Review*, 107(9):2784–2820. https://doi.org/10.1257/aer.20121266.

Brown, S. J. and Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1):3–31. https://doi.org/10.1016/0304-405X(85)90042-X.

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., and Raffo, A. (2020). The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, 109:38–59. https://doi.org/10.1016/j.jmoneco.2019.11.002.

Campbell, J. Y. and Shiller, R. J. (1988). The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *The Review of Financial Studies*, 1(3):195–228. https://doi.org/10.1093/rfs/1.3.195.

Cavallo, A., Gopinath, G., Neiman, B., and Tang, J. (2021). Tariff Pass-Through at the Border and at the Store: Evidence from US Trade Policy. *American Economic Review: Insights*, 3(1):19–34. https://doi.org/10.1257/aeri.20190536.

Child, T. B., Massoud, N., Schabus, M., and Zhou, Y. (2021). Surprise election for Trump connections. *Journal of Financial Economics*, 140(2):676–697. https://doi.org/10.1016/j.jfineco.2020.12.004.

Corden, W. M. (1966). The Structure of a Tariff System and the Effective Protective Rate. *Journal of Political Economy*, 74(3):221–237. https://doi.org/10.1086/259151.

Corrado, C. J. and Zivney, T. L. (1992). The Specification and Power of the Sign Test in Event Study Hypothesis Tests Using Daily Stock Returns. *Journal of Financial and Quantitative Analysis*, 27(3):465–478. https://doi.org/10.2307/2331331.

Cosma, S., Cosma, S., Gambarelli, L., Pennetta, D., and Rimo, G. (2025). Political elections and market reactions: The ‘Trump effect’ on green stocks. *Economics Letters*, 249:112261. https://doi.org/10.1016/j.econlet.2025.112261.

Egger, P. H. and Zhu, J. (2020). The US–Chinese trade war: an event study of stock-market responses. *Economic Policy*, 35(103):519–559. https://doi.org/10.1093/epolic/eiaa016.

Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J., and Khandelwal, A. K. (2020). The return to protectionism. *The Quarterly Journal of Economics*, 135(1):1–55. https://doi.org/10.1093/qje/qjz036.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, 25(2):383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56. https://doi.org/10.1016/0304-405X(93)90023-5.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22. https://doi.org/10.1016/j.jfineco.2014.10.010.

Ferriani, F., Gazzani, A., and Taboga, M. (2025). The impact of Trump's victory on equity markets: The power of proximity. *Economics Letters*, 247:112199. https://doi.org/10.1016/j.econlet.2025.112199.

Feyrer, J. (2019). Trade and Income–Exploiting Time Series in Geography. *American Economic Journal: Applied Economics*, 11(4):1–35. https://doi.org/10.1257/app.20170616.

Flaaen, A., Hortaçsu, A., and Tintelnot, F. (2020). The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines. *American Economic Review*, 110(7):2103–2127. https://doi.org/10.1257/aer.20190611.

Flaaen, A. and Pierce, J. R. (2024). Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector. *The Review of Economics and Statistics*, pages 1–45. https://doi.org/10.1162/rest_a_01498.

Frankel, J. A. and Romer, D. H. (1999). Does Trade Cause Growth? *American Economic Review*, 89(3):379–399. https://doi.org/10.1257/aer.89.3.379.

Greenland, A., Ion, M., Lopresti, J., and Schott, P. K. (2024). Using equity market reactions to infer exposure to trade liberalization. *Journal of International Economics*, 152:104000. https://doi.org/10.1016/j.jinteco.2024.104000.

Greenwald, D. L., Lettau, M., and Ludvigson, S. C. (2025). How the Wealth Was Won: Factor Shares as Market Fundamentals. *Journal of Political Economy*, 133(4):1083–1132. https://doi.org/10.1086/734089.

Grossman, G. M. and Helpman, E. (1994). Protection for sale. *The American Economic Review*, 84(4):833–850. https://www.jstor.org/stable/2118033.

Grossman, G. M., Helpman, E., and Redding, S. J. (2024). When Tariffs Disrupt Global Supply Chains. *American Economic Review*, 114(4):988–1029. https://doi.org/10.1257/aer.20211519.

Hadlock, C. J. and Pierce, J. R. (2010). New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *The Review of Financial Studies*, 23(5):1909–1940. https://doi.org/10.1093/rfs/hhq009.

Handley, K. and Limaõ, N. (2017). Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States. *American Economic Review*, 107(9):2731–2783. https://doi.org/10.1257/aer.20141419.

Huang, Y., Lin, C., Liu, S., and Tang, H. (2023). Trade networks and firm value: Evidence from the U.S.-China trade war. *Journal of International Economics*, 145:103811. https://doi.org/10.1016/j.jinteco.2023.103811.

Jones, R. W. (1975). Income distribution and effective protection in a multicommodity trade model. *Journal of Economic Theory*, 11(1):1–15. https://doi.org/10.1016/0022-0531(75)90035-6.

Kolari, J. W. and Pynnonen, S. (2011). Nonparametric rank tests for event studies. *Journal of Empirical Finance*, 18(5):953–971. https://doi.org/10.1016/j.jempfin.2011.08.003.

Krugman, P. R. (1991). *Geography and Trade*. MIT Press, Cambridge, MA.

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, 35(1):13–39. https://www.jstor.org/stable/2729691.

Manova, K. (2013). Credit Constraints, Heterogeneous Firms, and International Trade. *The Review of Economic Studies*, 80(2):711–744. https://doi.org/10.1093/restud/rds036.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725. https://doi.org/10.1111/1468-0262.00467.

Perla, J., Tonetti, C., and Waugh, M. E. (2021). Equilibrium Technology Diffusion, Trade, and Growth. *American Economic Review*, 111(1):73–128. https://doi.org/10.1257/aer.20151645.

Pierce, J. R. and Schott, P. K. (2016). The Surprisingly Swift Decline of US Manufacturing Employment. *American Economic Review*, 106(7):1632–1662. https://doi.org/10.1257/aer.20131578.

Siriopoulos, C., Spyridou, A., and Polyzos, E. (2025). Trump's Liberation Day Tariffs: A Framework for Economic Impact and Policy Assessment. *Available at SSRN*. https://dx.doi.org/10.2139/ssrn.5230022.

Topalova, P. and Khandelwal, A. (2011). Trade Liberalization and Firm Productivity: The Case of India. *Review of Economics and Statistics*, 93(3):995–1009. https://doi.org/10.1162/REST_a_00095.

Wacziarg, R. and Welch, K. H. (2008). Trade Liberalization and Growth: New Evidence. *The World Bank Economic Review*, 22(2):187–231. https://doi.org/10.1093/wber/lhn007.

Wagner, A. F., Zeckhauser, R. J., and Ziegler, A. (2018). Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. *Journal of Financial Economics*, 130(2):428–451. https://doi.org/10.1016/j.jfineco.2018.06.013.

Wengerek, S. T., Uhde, A., and Hippert, B. (2025). Share price reactions to tariff imposition announcements during the first Trump administration. *Finance Research Letters*, page 107381. https://doi.org/10.1016/j.frl.2025.107381.

Table 1 Descriptive statistics of cumulative abnormal returns, trade exposure variables, and firm characteristics.

This table reports comprehensive summary statistics for all variables used in the "Liberation Day 2025" tariff announcement analysis. Panel A reports cumulative abnormal return (CAR) across eleven event windows, calculated using the market model with parameters estimated over a 250-trading-day window ending 10 days before April 2, 2025. CAR is expressed in decimal. Panel B reports trade exposure measures: import intensity as the ratio of imported intermediate inputs to total intermediate inputs for each industry sector; export intensity as foreign revenue divided by total sales; supply chain complexity as an index from 1 to 5 combining three BEA Input-Output dimensions: number of distinct intermediate input categories, import intensity of those inputs, and Herfindahl concentration of purchases. Panel C reports firm characteristics measured as of fiscal year-end 2024: Log(total assets) as log of total assets in millions USD; leverage as total debt divided by total assets; cash ratio as cash and short-term equivalents divided by total assets; ROA as net income divided by total assets; financial constraint index, following Hadlock and Pierce (2010), as a composite index combining standardized leverage, cash ratio, ROA, and firm size, where higher index values indicate greater financial constraints from high leverage, low cash reserves, weak profitability, and small size. N indicates the number of firms and % Neg indicates % negative CAR during each event window.

Variable	**Mean**	**Std. Dev.**	**Median**	**% Neg**	**N**
Panel A: Cumulative abnormal return (CAR) by event window					
Around event windows					
$[-3, 3]$	-0.027	0.062	-0.033	91%	500
$[-3, 2]$	-0.021	0.057	-0.024	91%	500
$[-3, 1]$	-0.008	0.046	-0.004	73%	500
$[-2, 2]$	-0.021	0.054	-0.023	91%	500
$[-1, 1]$	-0.011	0.039	-0.007	82%	500
Pre-event windows					
$[-3, 0]$	0.005	0.023	0.007	27%	500
$[-3, -1]$	0.001	0.022	0.004	45%	500
$[-3, -2]$	0.003	0.019	0.004	27%	500
Post-event windows					
$[0, 1]$	-0.009	0.037	-0.003	73%	500
$[0, 2]$	-0.023	0.054	-0.026	82%	500
$[0, 3]$	-0.028	0.062	-0.035	91%	500
Panel B: Trade exposure variables					
Import Intensity	0.108	0.040	0.117	–	500
Export Intensity	0.211	0.123	0.190	–	500
Supply Chain Complexity	3.163	1.155	3.600	–	500
Panel C: Firm characteristics					
Log(Total Assets)	17.315	1.306	17.169	–	500
Leverage	0.301	0.246	0.281	–	500
Cash Ratio	0.099	0.130	0.065	–	500
ROA	0.078	0.091	0.057	–	500
Financial Constraint Index	0.011	1.925	0.213	–	500

Table 2 Aggregate market response to universal tariff announcement.

This table reports market-level average abnormal return (AAR) and cumulative abnormal return (CAR) for all S&P 500 constituents surrounding the April 2, 2025 "Liberation Day" tariff announcement. Panel A presents daily AAR for seven days centered on the event (Day 0). Day 0 represents the announcement date when President Trump announced a 10% universal baseline tariff on all imports plus elevated duties on major trading partners. Abnormal returns are calculated using the market model with parameters estimated over a 250-trading-day window ending 10 days before the event. Panel B reports CAR over seven theoretically important event windows consisting of around event windows, pre-event and post-event windows. AAR and CAR are expressed in percentage (%). The BMP statistic indicates the Boehmer et al. (1991) standardized cross-sectional test. WRank indicates the Wilcoxon signed-rank test for the null hypothesis that returns have a zero median. Complete daily results for all eleven event windows and for all eleven GIC sectors are presented in Appendix Table A.2. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Average abnormal return (AAR) over event days

Event day	AAR (%)	BMP	WRank	Obs
-3	-0.07	-1.84*	-1.86*	500
-2	0.36	9.30***	7.23***	500
-1	-0.16	-3.60***	-2.13**	500
0	0.41	7.03***	7.76***	500
+1	-1.31	-7.68***	-6.60***	500
+2	-1.31	-10.86***	-8.00***	500
+3	-0.54	-8.98***	-6.77***	500

Panel B: Cumulative abnormal return (CAR) over event windows

Event window	CAR (%)	BMP	WRank	Obs
$[-3, 3]$	-2.63	-13.54***	-10.50***	500
$[-2, 2]$	-2.01	-10.59***	-8.88***	500
$[-1, 1]$	-1.07	-6.66***	-5.55***	500
$[-3, -2]$	0.29	5.36***	4.64***	500
$[0, 1]$	-0.90	-5.87***	-4.55***	500
$[0, 2]$	-2.21	-12.25***	-9.71***	500
$[0, 3]$	-2.75	-14.23***	-10.62***	500

Table 3 Daily average abnormal returns (AARs) by industry sector around the tariff announcement.

This table reports industry-specific average daily abnormal return (AAR) for all S&P 500 constituents across 11 GICS sectors, formed based on SIC classification, for seven days surrounding the April 2, 2025 "Liberation Day" tariff announcement. Day 0 represents the announcement date. AAR is expressed in percentage (%). Abnormal returns are calculated using the market model with parameters estimated over a 250-trading-day window ending 10 days before the event. The BMP statistic indicates the Boehmer et al. (1991) standardized cross-sectional test. WRank indicates the Wilcoxon signed-rank test. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Sector	Event day						
	−3	−2	−1	0	+1	+2	+3
Communication Services							
AAR	-0.83	1.15	-0.73	-0.09	-0.97	-1.60	-0.43
BMP	-3.13***	3.15***	-1.99**	-0.03	-1.27	-2.24**	-1.46
WRank	-2.80***	2.46**	-1.46	-0.12	-0.64	-2.07**	-1.28
Obs	23	23	23	23	23	23	23
Consumer Discretionary							
AAR	-1.07	0.18	0.34	0.99	-2.45	2.84	-1.67
BMP	-4.32***	1.49	2.04**	4.42***	-3.22***	4.52***	-5.54***
WRank	-4.24***	1.21	1.73*	4.32***	-3.31***	4.21***	-4.34***
Obs	51	51	51	51	51	51	51
Consumer Staples							
AAR	-0.15	1.00	0.14	-0.17	0.85	-2.93	-1.21
BMP	-1.08	6.52***	0.81	-1.82*	2.38**	-7.25***	-4.96***
WRank	-0.79	4.46***	0.75	-1.31	2.75***	-4.15***	-4.04***
Obs	38	38	38	38	38	38	38
Energy							
AAR	0.60	0.73	0.58	0.13	-6.24	-6.15	-0.11
BMP	3.26***	5.35***	6.22***	0.45	-8.54***	-14.70***	-0.80
WRank	2.59***	3.86***	3.86***	1.00	-4.14***	-4.20***	-0.36
Obs	23	23	23	23	23	23	23
Financials							
AAR	-0.40	0.76	-0.34	0.51	-2.12	-2.70	-0.58
BMP	-3.92***	6.48***	-3.87***	3.93***	-5.96***	-8.04***	-3.05***
WRank	-4.92***	5.62***	-3.43***	3.86***	-4.88***	-5.82***	-2.46**
Obs	73	73	73	73	73	73	73
Health Care							
AAR	0.14	0.35	-1.39	0.49	0.49	-2.35	-0.28
BMP	1.36	3.16***	-5.95***	3.27***	1.58	-6.83***	-1.86*
WRank	1.27	3.72***	-6.11***	3.49***	1.49	-5.21***	-1.86*
Obs	60	60	60	60	60	60	60
Industrials							
AAR	-0.43	0.21	0.11	0.64	-1.87	-0.55	-0.62
BMP	-4.55***	3.00***	1.58	4.99***	-4.88***	-2.16**	-3.97***
WRank	-4.41***	1.95*	2.78***	5.19***	-4.33***	-1.50	-3.14***
Obs	76	76	76	76	76	76	76
Information Technology							
AAR	0.35	-0.75	-0.01	0.19	-0.89	1.49	1.71
BMP	0.41	-3.70***	-0.34	1.41	-2.29**	1.85*	4.04***
WRank	1.22	-4.60***	-0.07	1.58	-1.62	3.22***	4.06***
Obs	69	69	69	69	69	69	69
Materials							
AAR	-0.44	0.50	0.07	0.35	-1.84	-2.26	-1.15
BMP	-3.11***	3.00***	0.80	2.40**	-2.37**	-3.26***	-3.85***
WRank	-2.49**	2.17**	0.26	2.00**	-2.06**	-2.87***	-2.70***
Obs	25	25	25	25	25	25	25
Real Estate							
AAR	0.94	0.37	-0.29	0.28	-1.12	-1.81	-2.11
BMP	7.42***	2.06**	-2.42**	1.90*	-2.60***	-3.97***	-7.75***
WRank	4.41***	2.43**	-2.25**	1.74*	-2.29**	-3.19***	-4.21***
Obs	31	31	31	31	31	31	31
Utilities							
AAR	1.33	0.82	0.18	0.35	0.39	-3.86	-1.43
BMP	10.70***	5.77***	0.30	1.28	2.68***	-10.80***	-6.07***
WRank	4.84***	3.45***	0.24	1.41	1.31	-4.33***	-3.08***
Obs	31	31	31	31	31	31	31

Table 4 Cumulative abnormal returns (CARs) by industry sector over multiple event windows.

This table reports industry-specific average cumulative abnormal return (CAR) for all S&P 500 constituents across 11 GICS sectors, formed based on SIC classification, over each day in the event window. CAR is expressed in percentage (%). The BMP statistic indicates the Boehmer et al. (1991) standardized cross-sectional test. WRank indicates the Wilcoxon signed-rank test. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Sector	**Event window**						
	$[-3, 3]$	$[-2, 2]$	$[-1, 1]$	$[-3, -2]$	$[0, 1]$	$[0, 2]$	$[0, 3]$
Communication Services							
CAR	-3.33	-2.08	-1.62	0.31	-0.89	-2.49	-2.91
BMP	-3.03***	-2.02**	-1.91*	0.95	-1.55	-2.64***	-2.65***
WRank	-2.74***	-1.82*	-0.91	0.70	-0.46	-2.49**	-2.55**
Obs	23	23	23	23	23	23	23
Consumer Discretionary							
CAR	-0.84	1.90	-1.13	-0.89	-1.47	1.37	-0.30
BMP	-1.19	2.50**	-1.34	-1.89*	-1.81*	1.81*	-0.64
WRank	-1.00	2.28**	-1.47	-2.05**	-1.77*	1.82*	-0.27
Obs	51	51	51	51	51	51	51
Consumer Staples							
CAR	-2.46	-1.10	0.83	0.85	0.69	-2.24	-3.45
BMP	-4.19***	-2.34**	1.80*	5.47***	1.71*	-4.22***	-5.67***
WRank	-3.40***	-2.75***	1.65*	4.15***	1.76*	-3.66***	-3.95***
Obs	38	38	38	38	38	38	38
Energy							
CAR	-10.45	-10.94	-5.52	1.33	-6.11	-12.26	-12.37
BMP	-8.75***	-12.76***	-7.11***	7.53***	-8.04***	-13.54***	-11.00***
WRank	-4.11***	-4.20***	-3.95***	4.14***	-4.01***	-4.20***	-4.20***
Obs	23	23	23	23	23	23	23
Financials							
CAR	-4.87	-3.89	-1.95	0.35	-1.61	-4.31	-4.89
BMP	-12.27***	-12.92***	-6.28***	1.81*	-5.55***	-14.80***	-12.39***
WRank	-6.88***	-6.90***	-5.13***	1.34	-4.69***	-7.30***	-7.25***
Obs	73	73	73	73	73	73	73
Health Care							
CAR	-2.55	-2.41	-0.41	0.49	0.98	-1.38	-1.66
BMP	-4.23***	-4.07***	-1.04	3.21***	2.73***	-2.93***	-3.42***
WRank	-3.55***	-3.50***	-0.94	3.25***	2.89***	-2.42**	-2.72***
Obs	60	60	60	60	60	60	60
Industrials							
CAR	-2.51	-1.47	-1.12	-0.22	-1.23	-1.78	-2.40
BMP	-4.79***	-2.95***	-2.58***	-0.79	-3.29***	-4.31***	-5.24***
WRank	-4.37***	-2.87***	-2.18**	-1.16	-2.86***	-3.88***	-4.34***
Obs	76	76	76	76	76	76	76
Information Technology							
CAR	2.09	-0.03	-0.71	-0.41	-0.69	0.80	2.51
BMP	0.36	-1.45	-2.02**	-2.51**	-2.07**	2.52**	2.10**
WRank	1.44	-0.14	-1.24	-2.26**	-1.43	1.67*	2.14**
Obs	69	69	69	69	69	69	69
Materials							
CAR	-4.78	-3.19	-1.43	0.06	-1.50	-3.75	-4.90
BMP	-3.48***	-2.15**	-1.57	1.06	-1.92*	-2.99***	-4.10***
WRank	-3.27***	-2.44**	-1.74*	1.06	-1.87*	-2.97***	-3.43***
Obs	25	25	25	25	25	25	25
Real Estate							
CAR	-3.72	-2.56	-1.13	1.32	-0.84	-2.64	-4.75
BMP	-5.78***	-4.47***	-2.97***	5.99***	-2.51**	-5.36***	-7.36***
WRank	-3.92***	-3.47***	-2.43**	4.13***	-2.23**	-3.88***	-4.41***
Obs	31	31	31	31	31	31	31
Utilities							
CAR	-2.23	-2.12	0.92	2.14	0.74	-3.12	-4.55
BMP	-4.96***	-6.02***	4.39***	10.54***	4.20***	-8.29***	-8.24***
WRank	-2.98***	-3.80***	3.57***	4.78***	3.17***	-4.29***	-3.78***
Obs	31	31	31	31	31	31	31

Table 5 Aggregate valuation effects by sector from tariff announcement during the [0,2] event window.

This table reports aggregate valuation changes in billion USD by GICS sector following the April 2, 2025 universal tariff announcement. Valuation change is calculated as the product of cumulative abnormal return and pre-announcement market capitalization for each firm, then summed within sectors. These figures represent shareholder wealth effects and anticipated changes in firm profitability, not broader social welfare which would require accounting for consumer surplus, tariff revenue redistribution, and general equilibrium effects. Firms in the third column indicates number of firms. Sector CARs are equal-weighted averages across firms. Negative values indicate markets anticipate reduced future cash flows. Sectors are ranked by absolute magnitude of wealth impact.

Sector	Sector CAR [0,2] (%)	Firms	Aggregate Value (USD billion)	Rank
Aggregate valuation gainers:				
Information Technology	0.80	69	459.12	1
Consumer Discretionary	1.37	51	236.90	3
Aggregate valuation losers:				
Financials	-4.31	73	-305.87	2
Energy	-12.26	23	-210.29	4
Industrials	-1.78	76	-109.48	5
Health Care	-1.38	60	-108.72	6
Consumer Staples	-2.24	38	-76.97	7
Utilities	-3.12	31	-38.10	8
Materials	-3.75	25	-29.07	9
Real Estate	-2.64	31	-25.15	10
Communication Services	-2.49	23	-24.07	11
Aggregate impact:				
Total Market	-2.21***	500	-183.55	

Table 6 Size-based market response to universal tariff announcement.

This table reports size-based average abnormal return (AAR) and cumulative abnormal return (CAR) for tercile portfolios of S&P 500 constituents surrounding the April 2, 2025 "Liberation Day" tariff announcement. Firms are sorted into terciles based on market capitalization measured over the estimation period. Panel A presents daily AAR for seven days centered on the event (Day 0). Panel B reports CAR over seven event windows. Small firms represent the bottom tercile (lowest market cap), medium firms the middle tercile, and large firms the top tercile (highest market cap). Portfolio returns are calculated as equal-weighted averages across firms in each size tercile.Abnormal returns are calculated using the market model with parameters estimated over a 250-trading-day window ending 10 days before the event. AAR and CAR are expressed in percentage (%). The BMP statistic indicates the Boehmer et al. (1991) standardized cross-sectional test. WRank indicates the Wilcoxon signed-rank test. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Average abnormal return (AAR) over event days

Firm Size	**Event day**						
	−3	−2	−1	0	+1	+2	+3
Small firms							
AAR	0.01	0.42	-0.28	0.67	-2.09	-0.89	-0.96
BMP	0.59	5.49***	-2.86***	6.43***	-6.99***	-4.54***	-7.44***
WRank	0.38	4.69***	-2.56**	6.30***	-6.03***	-3.55***	-6.05***
Obs	167	167	167	167	167	167	167
Medium firms							
AAR	-0.13	0.41	-0.05	0.38	-1.34	-1.59	-0.64
BMP	-1.33	5.67***	-0.83	4.83***	-4.45***	-7.10***	-5.88***
WRank	-1.21	4.71***	-0.09	5.05***	-3.88***	-5.35***	-4.12***
Obs	167	167	167	167	167	167	167
Large Firms							
AAR	-0.09	0.26	-0.16	0.18	-0.50	-1.44	-0.03
BMP	-2.49**	4.95***	-2.34**	1.38	-1.89*	-7.09***	-2.56**
WRank	-1.75*	3.01***	-1.04	2.03**	-1.33	-4.89***	-1.54
Obs	166	166	166	166	166	166	166

Panel B: Cumulative abnormal return (CAR) over event windows

Firm Size	**Event window**						
	$[-3, 3]$	$[-2, 2]$	$[-1, 1]$	$[-3, -2]$	$[0, 1]$	$[0, 2]$	$[0, 3]$
Small Firms							
CAR	-3.12	-2.17	-1.70	0.42	-1.42	-2.31	-3.27
BMP	-157.27***	-116.61***	-104.89***	78.32***	-95.15***	-130.85***	-164.60***
WRank	-123.16***	-100.81***	-89.70***	59.63***	-79.63***	-110.91***	-128.03***
Obs	167	167	167	167	167	167	167
Medium Firms							
CAR	-2.97	-2.20	-1.01	0.27	-0.96	-2.55	-3.19
BMP	-147.73***	-111.01***	-61.17***	50.06***	-60.30***	-133.02***	-161.16***
WRank	-118.26***	-97.23***	-52.61***	51.44***	-46.86***	-105.20***	-119.68***
Obs	167	167	167	167	167	167	167
Large Firms							
CAR	-1.80	-1.67	-0.48	0.17	-0.32	-1.77	-1.80
BMP	-120.46***	-103.92***	-41.85***	40.18***	-27.12***	-119.05***	-120.75***
WRank	-85.25***	-77.91***	-27.45***	32.72***	-11.95***	-86.17***	-82.04***
Obs	166	166	166	166	166	166	166

Table 7 Portfolio sorts by import intensity.

This table presents cumulative abnormal return (CAR) for all S&P 500 firms in portfolios sorted by import intensity following President Trump's tariff announcement on April 2, 2025. Panel A reports results for tercile portfolios, where firms are sorted into three groups based on their import intensity, calculated as the ratio of imported intermediate inputs to total intermediate inputs at the industry level. Panel B reports results for quintile portfolios, where firms are divided into five groups. Q1 denotes the lowest import and Q5 denotes the highest import. For each portfolio in both panels, we report the mean CAR over selected event windows. Portfolio returns are calculated as equal-weighted averages of all firms within each import intensity tercile (Panel A) or quintile (Panel B). The final row in each panel shows the difference in CARs between high and low import intensity portfolios with t-statistics in parentheses from two-sample t-tests. The linear trend coefficient comes from regressing CAR on quintile rank (1 through 5) and tests for a monotonic relationship across portfolios, using information from all five quintiles. CARs are calculated using the market model with parameters estimated over a 250-trading-day window ending 10 days before the event. All values are in decimal form. Standard errors are robust. Portfolio sizes are unequal due to ties in import intensity values. When multiple firms share the same import intensity value at a tercile or quintile boundary, they are assigned to the same tercile or quintile, following standard methodology (Fama and French, 1993). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolios sorted in terciles

Portfolio	Mean CAR over event window						
	$[-3,3]$	$[-2,2]$	$[-1,1]$	$[-3,-2]$	$[0,1]$	$[0,2]$	$[0,3]$
1 (Low import, N=180)	-0.048	-0.041	-0.017	0.009	-0.016	-0.046	-0.056
2 (Medium import, N=222)	-0.027	-0.020	-0.007	0.008	-0.009	-0.030	-0.034
3 (High import, N=98)	0.004	-0.008	-0.008	-0.003	-0.008	-0.003	0.007
Difference (3-1)	0.052***	0.033***	0.009*	-0.012***	0.008*	0.043***	0.063***
	(6.51)	(5.22)	(1.91)	(-5.98)	(1.65)	(6.61)	(8.17)

Panel B: Portfolios sorted in quintiles

Portfolio	Mean CAR over event window						
	$[-3,3]$	$[-2,2]$	$[-1,1]$	$[-3,-2]$	$[0,1]$	$[0,2]$	$[0,3]$
Q1 (Lowest import, N=103)	-0.042	-0.035	-0.011	0.008	-0.009	-0.040	-0.049
Q2 (N=137)	-0.043	-0.038	-0.016	0.008	-0.009	-0.037	-0.044
Q3 (N=86)	-0.018	0.005	-0.004	-0.001	-0.006	-0.004	-0.019
Q4 (N=76)	-0.025	-0.015	-0.011	-0.002	-0.012	-0.018	-0.024
Q5 (Highest import, N=98)	0.004	-0.008	-0.008	-0.003	-0.008	-0.003	0.007
Difference (Q5-Q1)	0.046***	0.027***	0.003*	-0.011**	0.001*	0.037***	0.056***
	(2.99)	(2.75)	(1.66)	(-3.37)	(1.72)	(3.11)	(4.01)
Linear Trend Coef.	0.010***	0.006***	0.000	-0.004***	0.001	0.008***	0.012***
	(4.73)	(3.38)	(0.06)	(-5.80)	(0.82)	(4.27)	(6.12)

Table 8 Mechanism tests by profitability and financial constraints.

This table examines two potential mechanisms through which import intensity affects stock returns following President Trump's tariff announcement on April 2, 2025. Panel A shows separate regression results for selected event windows using FC index, High ROA, Import intensity + FC index and Import intensity + High ROA. Panel B tests a profitability or adjustment-capacity channel by including an interaction term between import intensity and a high profitability indicator (ROA > 10%). Panel C tests the financial constraints hypothesis by including an interaction term between import intensity and a standardized financial constraint index. The dependent variable is the CAR for different event windows. Import intensity is calculated as the ratio of imported intermediate inputs to total intermediate inputs for each industry sector. High ROA is an indicator variable equal to one if the firm's return on assets exceeds 10%. FC index, following Hadlock and Pierce (2010), is a composite measure combining standardized leverage (debt/assets), cash ratio (cash/assets), ROA (net income/assets), and log assets, with higher values indicating greater constraints. All specifications include Log(Assets), which is the natural logarithm of total assets measured in millions of dollars, as a control variable. Standard errors are clustered at the industry level to account for the industry-level measurement of import intensity. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Level effects without interaction

Variables	Cumulative abnormal return (CAR) over event windows					
	$[-3,3]$	$[-2,2]$	$[-1,1]$	$[0,2]$	$[0,3]$	$[-3,0]$
(1) FC Index only:						
FC Index	-0.022***	-0.022***	-0.007	-0.017***	-0.018***	-0.002
	(-3.53)	(-4.50)	(-1.72)	(-3.17)	(-2.88)	(-0.47)
(2) High ROA only:						
High ROA	0.025***	0.026***	0.010**	0.022***	0.024***	-0.002
	(3.67)	(4.36)	(2.21)	(3.69)	(3.64)	(-0.61)
(3) Import Intensity + FC Index (no interaction):						
Import Intensity	0.178**	0.167**	-0.003	0.221***	0.295***	-0.113***
	(2.35)	(2.54)	(-0.07)	(3.35)	(4.06)	(-4.45)
FC Index	-0.021***	-0.020***	-0.007*	-0.015***	-0.015**	-0.003
	(-3.22)	(-4.12)	(-1.69)	(-2.72)	(-2.38)	(-0.79)
(4) Import Intensity + High ROA (no interaction):						
Import Intensity	0.182**	0.169**	-0.004	0.219***	0.292***	-0.108***
	(2.44)	(2.64)	(-0.10)	(3.43)	(4.11)	(-4.25)
High ROA	0.023***	0.024***	0.010**	0.020***	0.021***	-0.001
	(3.41)	(4.06)	(2.20)	(3.32)	(3.21)	(-0.19)

Panel B: Profitability mechanism

Variables	Cumulative abnormal return (CAR) over event windows					
	$[-3,3]$	$[-2,2]$	$[-1,1]$	$[0,2]$	$[0,3]$	$[-3,0]$
Import Intensity	0.144*	0.133*	-0.018	0.198***	0.290***	-0.157***
	(1.74)	(1.89)	(-0.38)	(2.83)	(3.61)	(-5.65)
High ROA Dummy	-0.026	-0.015	-0.003	-0.013	-0.007	-0.033***
	(-1.35)	(-0.76)	(-0.27)	(-0.67)	(-0.33)	(-4.14)
Import $\times$ High ROA	0.460***	0.350**	0.118	0.319**	0.307*	0.249***
	(2.75)	(2.27)	(1.19)	(1.99)	(1.73)	(3.87)
Log(Assets)	-0.002	-0.003	-0.002	-0.003	-0.001	-0.003***
	(-1.03)	(-1.17)	(-1.19)	(-1.49)	(-1.53)	(-3.69)
Observations	500	500	500	500	500	500
R-squared	0.104	0.126	0.029	0.126	0.129	0.064

Panel C: Financial constraints mechanism

Variables	Cumulative abnormal return (CAR) over event windows					
	$[-3,3]$	$[-2,2]$	$[-1,1]$	$[0,2]$	$[0,3]$	$[-3,0]$
Import Intensity	0.221***	0.198***	0.024	0.251***	0.319***	-0.099***
	(2.85)	(2.91)	(0.54)	(3.67)	(4.24)	(-3.76)
FC Index	0.004	-0.001	0.009*	0.001	-0.007	0.010***
	(0.51)	(-0.13)	(1.82)	(0.08)	(-1.00)	(3.56)
Import $\times$ FC Index	-0.188***	-0.099	-0.106**	-0.126**	-0.112*	-0.070***
	(-2.70)	(-1.63)	(-2.34)	(-2.09)	(-1.67)	(-2.80)
Log(Assets)	-0.008***	-0.009***	-0.003**	-0.008***	-0.008***	-0.001
	(-2.83)	(-3.27)	(-2.29)	(-3.99)	(-4.73)	(-0.87)
Observations	500	500	500	500	500	500
R-squared	0.138	0.122	0.028	0.148	0.184	0.061

Table 9 Cross-Sectional determinants of cumulative abnormal return (CAR).

This table presents cross-sectional regression results examining the determinants of cumulative abnormal return (CAR) for all S&P 500 firms following President Trump's tariff announcement on April 2, 2025. The dependent variable is the CAR for different event windows. Import intensity is calculated as the ratio of imported intermediate inputs to total intermediate inputs for each industry sector. Log(total assets) is measured as log of total assets in millions USD. Leverage is calculated as total debt divided by total assets. Cash ratio is measured as cash and short-term equivalents divided by total assets. All independent variables are measured as of the most recent fiscal year-end prior to the event. Each column represents a separate cross-sectional regression. Standard errors are clustered at the industry level to account for the industry-level measurement of import intensity. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	**Cumulative abnormal return (CAR) over event windows**					
	$[-3,3]$	$[-2,2]$	$[-1,1]$	$[0,2]$	$[0,3]$	$[-3,0]$
Import Intensity	0.211***	0.200***	0.008	0.244***	0.319***	-0.108***
	(2.79)	(3.06)	(0.19)	(3.77)	(4.42)	(-4.30)
Log(Assets)	-0.003**	-0.005**	-0.002**	-0.004**	-0.002**	-0.003***
	(-2.04)	(-2.41)	(-1.97)	(-1.96)	(-2.15)	(-3.53)
Cash Ratio	0.111***	0.074***	0.027**	0.092***	0.137***	-0.026***
	(4.77)	(3.99)	(1.96)	(4.81)	(5.92)	(-2.60)
Leverage	-0.015	-0.002	0.009	-0.010	-0.023**	0.003
	(-1.51)	(-0.24)	(1.37)	(-1.18)	(-2.23)	(0.71)
Constant	0.002	0.033	0.025	0.012	-0.042	0.066***
	(0.08)	(1.26)	(1.43)	(0.47)	(-1.49)	(6.50)
Observations	500	500	500	500	500	500
R-squared	0.110	0.101	0.023	0.132	0.176	0.063

Table 10 Comparison of market reactions: "2025 universal tariffs" vs "2018 targeted tariffs".

This table compares cumulative abnormal return (CAR) of overall market and across all 11 GICS sectors, formed based on SIC classification, between President Trump's April 2, 2025 "Liberation Day" universal tariff announcement (10% baseline on all imports plus elevated duties on major trading partners) and the March 23, 2018 "Targeted China" tariff announcement (25% on $50 billion of Chinese imports). We report CAR for three key event windows: [-1,1] which indicates standard three-day window, [0,2] which indicates post-announcement adjustment, and [-3,3] which indicates extended window. CAR is expressed in percentage (%). Complete daily, window- and industry-specific results for 2018 tariff announcement are presented in Appendix Tables A.13 and A.14. BMP test statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels for both samples using BMP tests.

Sector	**2025 universal tariffs**			**2018 targeted tariffs**		
	$[-1, 1]$	$[0, 2]$	$[-3, 3]$	$[-1, 1]$	$[0, 2]$	$[-3, 3]$
Overall Market	-1.07***	-2.21***	-2.63***	-0.14	0.13**	0.38***
	(-6.66)	(-12.25)	(-13.54)	(-0.87)	(1.99)	(2.82)
Communication Services	-1.62*	-2.49***	-3.33***	-0.04	-0.25	-1.04
	(-1.91)	(-2.64)	(-3.03)	(-0.10)	(-0.54)	(-1.58)
Consumer Discretionary	-1.13	1.37*	-0.84	0.06	0.47	0.65
	(-1.34)	(1.81)	(-1.19)	(0.25)	(1.64)	(1.42)
Consumer Staples	0.83*	-2.24***	-2.46***	-0.36	1.48***	1.53***
	(1.80)	(-4.22)	(-4.19)	(-0.84)	(3.38)	(3.51)
Energy	-5.52***	-12.26***	-10.45***	1.65**	-0.44	3.07***
	(-7.11)	(-13.54)	(-8.75)	(2.08)	(-0.52)	(3.19)
Financials	-1.95***	-4.31***	-4.87***	-1.03***	-0.57***	-0.77***
	(-6.28)	(-14.80)	(-12.27)	(-5.17)	(-2.65)	(-2.69)
Health Care	-0.41	-1.38***	-2.55***	-0.32	-0.11	0.35
	(-1.04)	(-2.93)	(-4.23)	(-1.38)	(-0.44)	(0.43)
Industrials	-1.12***	-1.78***	-2.51***	-0.19	-0.23	0.11
	(-2.58)	(-4.31)	(-4.79)	(-0.94)	(-1.06)	(0.41)
Information Technology	-0.71**	0.80**	2.09	-0.14	-1.24***	-1.66***
	(-2.02)	(2.52)	(0.36)	(-0.49)	(-3.92)	(-4.26)
Materials	-1.43	-3.75***	-4.78***	0.91*	1.39**	-0.31
	(-1.57)	(-2.99)	(-3.48)	(1.77)	(2.50)	(-0.19)
Real Estate	-1.13***	-2.64***	-3.72***	0.64**	2.43***	3.13***
	(-2.97)	(-5.36)	(-5.78)	(2.18)	(8.46)	(8.46)
Utilities	0.92***	-3.12***	-2.23***	1.11***	1.92***	3.26***
	(4.39)	(-8.29)	(-4.96)	(3.31)	(5.87)	(9.67)
Observations	500	500	500	475	475	475
% Negative CAR	82%	82%	91%	55%	55%	36%

Appendix Tables

Table A.1 Firm characteristics by sector.

This table reports mean firm characteristics by 11 GICS sectors, formed based on SIC classification. Log(Total Assets) is the natural logarithm of total assets in million dollars. Leverage is total debt divided by total assets. Cash ratio is cash and short-term equivalents divided by total assets. ROA is return on assets which is calculated as net income divided by total assets.

Sector	Log(Total Assets)	Leverage	Cash Ratio	ROA	N
Communication Services	17.87	0.37	0.07	0.06	23
Consumer Discretionary	17.22	0.30	0.13	0.10	51
Consumer Staples	17.65	0.32	0.06	0.09	38
Energy	17.36	0.26	0.04	0.08	23
Financials	18.54	0.23	0.07	0.03	73
Health Care	16.95	0.28	0.17	0.10	60
Industrials	16.98	0.30	0.08	0.09	76
Information Technology	16.77	0.22	0.19	0.12	69
Materials	17.00	0.34	0.07	0.07	25
Real Estate	16.77	0.50	0.03	0.04	31
Utilities	17.28	0.43	0.02	0.04	31
All Sectors	17.32	0.30	0.10	0.08	500

Table A.2 Overall and industry-based cumulative abnormal return (CAR) over the event windows.

This table reports the average cumulative abnormal return (CAR) for 500 stocks in the S&P 500 Index over each day in the event window. Alongside, industry-specific CAR for sample stocks across 11 GICS sectors, formed based on SIC classification, are reported. CAR is expressed in percentage (%). Statistical significance is tested using BMP and Wilcoxon signed-rank tests. Statistical significance: ***, **, * indicate 1%, 5% and 10% levels.

	$[-3,3]$	$[-3,2]$	$[-3,1]$	$[-2,2]$	$[-1,1]$	$[-3,0]$	$[-3,-1]$	$[-3,-2]$	$[0,1]$	$[0,2]$	$[0,3]$
Overall Market											
CAR	-2.63	-2.08	-0.78	-2.01	-1.07	0.54	0.12	0.29	-0.90	-2.21	-2.75
BMP	-13.54***	-10.79***	-3.36***	-10.59***	-6.66***	6.10***	2.73***	5.36***	-5.87***	-12.25***	-14.23***
WRank	-10.50***	-8.99***	-3.14***	-8.88***	-5.55***	6.38***	3.08***	4.64***	-4.55***	-9.71***	-10.62***
Obs	500	500	500	500	500	500	500	500	500	500	500
Communication Services											
CAR	-3.33	-2.91	-1.31	-2.08	-1.62	-0.33	-0.42	0.31	-0.89	-2.49	-2.91
BMP	-3.03***	-2.85***	-1.72*	-2.02**	-1.91*	-0.34	-0.45	0.95	-1.55	-2.64***	-2.65***
WRank	-2.74***	-2.37**	-1.16	-1.82*	-0.91	-0.85	-0.76	0.70	-0.46	-2.49**	-2.55**
Obs	23	23	23	23	23	23	23	23	23	23	23
Consumer Discretionary											
CAR	-0.84	0.83	-2.01	1.90	-1.13	0.44	-0.54	-0.89	-1.47	1.37	-0.30
BMP	-1.19	1.08	-1.92*	2.50**	-1.34	0.87	-1.04	-1.89*	-1.81*	1.81*	-0.64
WRank	-1.00	0.98	-2.07**	2.28**	-1.47	1.41	-0.58	-2.05**	-1.77*	1.82*	-0.27
Obs	51	51	51	51	51	51	51	51	51	51	51
Consumer Staples											
CAR	-2.46	-1.25	1.68	-1.10	0.83	0.83	0.99	0.85	0.69	-2.24	-3.45
BMP	-4.19***	-2.40**	3.40***	-2.34**	1.80*	2.64***	5.59***	5.47***	1.71*	-4.22***	-5.67***
WRank	-3.40***	-2.82***	2.72***	-2.75***	1.65*	2.94***	4.33***	4.15***	1.76*	-3.66***	-3.95***
Obs	38	38	38	38	38	38	38	38	38	38	38
Energy											
CAR	-10.45	-10.34	-4.19	-10.94	-5.52	2.05	1.92	1.33	-6.11	-12.26	-12.37
BMP	-8.75***	-10.54***	-4.68***	-12.76***	-7.11***	7.59***	9.62***	7.53***	-8.04***	-13.54***	-11.00***
WRank	-4.11***	-4.20***	-3.35***	-4.20***	-3.95***	4.20***	4.20***	4.14***	-4.01***	-4.20***	-4.20***
Obs	23	23	23	23	23	23	23	23	23	23	23
Financials											
CAR	-4.87	-4.29	-1.59	-3.89	-1.95	0.53	0.02	0.35	-1.61	-4.31	-4.89
BMP	-12.27***	-13.14***	-4.06***	-12.92***	-6.28***	2.22**	-0.13	1.81*	-5.55***	-14.80***	-12.39***
WRank	-6.88***	-6.85***	-3.75***	-6.90***	-5.13***	2.34**	-0.94	1.34	-4.69***	-7.30***	-7.25***
Obs	73	73	73	73	73	73	73	73	73	73	73
Health Care											
CAR	-2.55	-2.27	0.09	-2.41	-0.41	-0.41	-0.89	0.49	0.98	-1.38	-1.66
BMP	-4.23***	-3.81***	0.38	-4.07***	-1.04	-1.16	-2.53**	3.21***	2.73***	-2.93***	-3.42***
WRank	-3.55***	-3.31***	0.24	-3.50***	-0.94	-0.52	-2.01**	3.25***	2.89***	-2.42**	-2.72***
Obs	60	60	60	60	60	60	60	60	60	60	60
Industrials											
CAR	-2.51	-1.89	-1.34	-1.47	-1.12	0.53	-0.11	-0.22	-1.23	-1.78	-2.40
BMP	-4.79***	-3.66***	-2.40**	-2.95***	-2.58***	2.67***	0.15	-0.79	-3.29***	-4.31***	-5.24***
WRank	-4.37***	-3.55***	-2.34**	-2.87***	-2.18**	2.79***	-0.01	-1.16	-2.86***	-3.88***	-4.34***
Obs	76	76	76	76	76	76	76	76	76	76	76
Information Technology											
CAR	2.09	0.38	-1.11	0.03	-0.71	-0.23	-0.42	-0.41	-0.69	0.80	2.51
BMP	0.36	-1.25	-2.72***	-1.45	-2.02**	-1.76*	-2.51**	-2.51**	-2.07**	-0.52	1.10
WRank	1.44	0.03	-1.77*	-0.14	-1.24	-0.98	-1.93*	-2.26**	-1.43	0.67	2.14**
Obs	69	69	69	69	69	69	69	69	69	69	69
Materials											
CAR	-4.78	-3.63	-1.37	-3.19	-1.43	0.47	0.12	0.06	-1.50	-3.75	-4.90
BMP	-3.48***	-2.33**	-1.07	-2.15**	-1.57	2.25**	1.22	1.06	-1.92*	-2.99***	-4.10***
WRank	-3.27***	-2.52**	-1.20	-2.44**	-1.74*	1.52	0.50	1.06	-1.87*	-2.97***	-3.43***
Obs	25	25	25	25	25	25	25	25	25	25	25
Real Estate											
CAR	-3.72	-1.62	0.19	-2.56	-1.13	1.31	1.03	1.32	-0.84	-2.64	-4.75
BMP	-5.78***	-3.22***	0.23	-4.47***	-2.97***	6.02***	4.53***	5.99***	-2.51**	-5.36***	-7.36***
WRank	-3.92***	-2.55**	0.24	-3.47***	-2.43**	4.15***	3.66***	4.13***	-2.23**	-3.88***	-4.41***
Obs	31	31	31	31	31	31	31	31	31	31	31
Utilities											
CAR	-2.23	-0.80	3.07	-2.12	0.92	2.68	2.32	2.14	0.74	-3.12	-4.55
BMP	-4.96***	-2.59***	10.69***	-6.02***	4.39***	13.09***	13.17***	10.54***	4.20***	-8.29***	-8.24***
WRank	-2.98***	-2.08**	4.84***	-3.80***	3.57***	4.86***	4.86***	4.78***	3.17***	-4.29***	-3.78***
Obs	31	31	31	31	31	31	31	31	31	31	31

Table A.3 Size-based cumulative abnormal return (CAR) over the event windows.

This table reports the cumulative abnormal return (CAR) for size-based tercile portfolios of all S&P 500 constituents. CAR is expressed in percentage (%). Size-based tercile portfolios are formed using average market value over the estimation period. Small firms indicate the bottom tercile, Medium firms indicate the middle tercile and Large firms indicate the top tercile. Statistical significance is tested using BMP and Wilcoxon signed-rank tests. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Firm	$[-3,3]$	$[-3,2]$	$[-3,1]$	$[-2,2]$	$[-1,1]$	$[-3,0]$	$[-3,-1]$	$[-3,-2]$	$[0,1]$	$[0,2]$	$[0,3]$
Small Firms											
CAR	-3.12	-2.17	-1.28	-2.17	-1.70	0.81	0.14	0.42	-1.42	-2.31	-3.27
BMP	-157.27***	-113.41***	-59.90***	-116.61***	-104.89***	99.16***	39.10***	78.32***	-95.15***	-130.85***	-164.60***
WRank	-123.16***	-99.54***	-59.04***	-100.81***	-89.70***	86.20***	31.03***	59.63***	-79.63***	-110.91***	-128.03***
Obs	167	167	167	167	167	167	167	167	167	167	167
Medium Firms											
CAR	-2.97	-2.33	-0.74	-2.20	-1.01	0.60	0.22	0.27	-0.96	-2.55	-3.19
BMP	-147.73***	-112.14***	-26.70***	-111.01***	-61.17***	73.57***	38.88***	50.06***	-60.30***	-133.02***	-161.16***
WRank	-118.26***	-97.40***	-23.91***	-97.23***	-52.61***	83.31***	49.08***	51.44***	-46.86***	-105.20***	-119.68***
Obs	167	167	167	167	167	167	167	167	167	167	167
Large Firms											
CAR	-1.80	-1.77	-0.32	-1.67	-0.48	0.18	0.00	0.17	-0.32	-1.77	-1.80
BMP	-120.46***	-112.43***	-19.12***	-103.92***	-41.85***	19.23***	6.00***	40.18***	-27.12***	-119.05***	-120.75***
WRank	-85.25***	-84.52***	-14.71***	-77.91***	-27.45***	24.58***	14.28***	32.72***	-11.95***	-86.17***	-82.04***
Obs	166	166	166	166	166	166	166	166	166	166	166

Table A.4 Correlation matrix of key variables.

This table reports Pearson correlation coefficients among the main variables used in the cross-sectional analysis. CAR $[0, 2]$ is the cumulative abnormal return over the three-day event window starting from the announcement day (Day 0). Import intensity is calculated as the ratio of imported intermediate inputs to total intermediate inputs for each industry sector. Export intensity is measured as foreign revenue divided by total sales. Supply chain complexity is an index from 1 to 5 combining three BEA Input-Output dimensions: number of distinct intermediate input categories, import intensity of those inputs, and Herfindahl concentration of purchases. Log(total assets) represents log of total assets in millions USD. Leverage is calculated as total debt divided by total assets. Cash ratio is cash and short-term equivalents divided by total assets. ROA is calculated as net income divided by total assets. Financial constraint index, following Hadlock and Pierce (2010), is a composite index combining standardized leverage, cash ratio, ROA, and firm size, where higher index values indicate greater financial constraints from high leverage, low cash reserves, weak profitability, and small size. * indicates statistical significance at the 5% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) CAR $[0, 2]$	1.000								
(2) Import Intensity	0.262*	1.000							
(3) Export Intensity	0.250*	0.818*	1.000						
(4) Supply Chain Complexity	0.316*	0.832*	0.883*	1.000					
(5) Log(total assets)	-0.211*	-0.386*	-0.329*	-0.380*	1.000				
(6) Leverage	-0.047	0.029*	-0.062*	0.029*	-0.170*	1.000			
(7) Cash Ratio	0.288*	0.219*	0.292*	0.345*	-0.251*	-0.101*	1.000		
(8) ROA	0.261*	0.271*	0.288*	0.354*	-0.356*	0.142*	0.352*	1.000	
(9) FC Index	-0.197*	-0.037*	-0.159*	-0.147*	-0.295*	0.586*	-0.613*	-0.443*	1.000

Table A.5 Portfolio sorts by financial constraints.

This table presents cumulative abnormal return (CAR) for all S&P 500 firms in portfolios sorted by financial constraints following President Trump's tariff announcement on April 2, 2025. Firms are sorted into terciles based on a composite financial constraint index created following (Hadlock and Pierce, 2010). This index is a composite measure combining standardized leverage (debt/assets), cash ratio (cash/assets), ROA (net income/assets), and log assets, with higher values indicating greater constraints. For each tercile, we report the mean CAR over selected event windows. Returns are calculated as equal-weighted averages across firms in each tercile. The final row shows the CAR difference between high and low constraint portfolios with t-statistics in parentheses from two-sample t-tests. CARs are calculated using the market model with parameters estimated over a 250-trading-day window ending 10 days before the event. All values are in decimal form. Standard errors are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Portfolio	**Mean CAR over event window**						
	$[-3, 3]$	$[-2, 2]$	$[-1, 1]$	$[-3, -2]$	$[0, 1]$	$[0, 2]$	$[0, 3]$
1 (Low constraint, N=166)	-0.012	-0.011	-0.009	-0.001	-0.008	-0.012	-0.010
2 (Medium constraint, N=168)	-0.027	-0.024	-0.009	-0.001	-0.008	-0.023	-0.030
3 (High constraint, N=166)	-0.032	-0.022	-0.010	0.007	-0.008	-0.025	-0.037
Difference (3-1)	-0.020***	-0.011**	-0.001	0.008***	0.000*	-0.013**	-0.027***
	(-3.06)	(-1.96)	(-0.15)	(4.01)	(1.67)	(-2.34)	(-4.28)

Table A.6 Robustness of import intensity effects to energy and financial sectors exclusions.

This table examines the robustness of the import intensity effect to sample composition by sequentially excluding firms from the energy and financials sectors. These sectors may have unique characteristics that could drive the main results. Column (1) presents results for the full sample. Column (2) excludes energy sector firms. Column (3) excludes financials sector firms. Column (4) excludes both energy and financials firms. The dependent variable is the cumulative abnormal return (CAR) for different event windows. Each panel-column represents a separate cross-sectional regression with import intensity as the key independent variable, controlling for Log(Assets), cash ratio and leverage. Import intensity is calculated as the ratio of imported intermediate inputs to total intermediate inputs for each industry sector. Log(Assets) is the natural logarithm of total assets measured in millions of dollars. Cash ratio is cash and short-term investments divided by total assets. Leverage is calculated as total debt divided by total assets. We report only the coefficient estimate and *t*-statistic for import intensity. Standard errors are clustered at the industry level to account for the industry-level measurement of import intensity ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Window	**Full Sample**		**Excl. Energy**		**Excl. Financials**		**Excl. Both**	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: Pre-announcement windows								
$[-3,-2]$	-0.124***	-6.20	-0.117***	-5.70	-0.163***	-7.09	-0.156***	-6.36
$[-3,-1]$	-0.108***	-4.63	-0.092***	-3.87	-0.143***	-5.28	-0.118***	-4.13
$[-3,0]$	-0.108***	-4.30	-0.094***	-3.66	-0.141***	-4.78	-0.120***	-3.81
Panel B: Around event windows								
$[-3,3]$	0.211***	2.79	0.146*	1.95	0.130	1.48	-0.009	-0.10
$[-3,2]$	0.136*	1.95	0.057	0.84	0.076	0.91	-0.083	-1.09
$[-3,1]$	-0.116**	-2.26	-0.154***	-3.02	-0.168***	-2.83	-0.250***	-4.33
$[-2,2]$	0.200***	3.06	0.115*	1.84	0.184**	2.34	0.022	0.30
$[-1,1]$	0.008	0.19	-0.036	-0.86	-0.005	-0.10	-0.094*	-1.91
Panel C: Post-announcement windows								
$[0,1]$	-0.008	-0.20	-0.062	-1.61	-0.025	-0.52	-0.132***	-3.07
$[0,2]$	0.244***	3.77	0.148**	2.43	0.219***	2.81	0.035	0.51
$[0,3]$	0.319***	4.42	0.237***	3.37	0.274***	3.20	0.109	1.39
Observations	500		477		427		404	

Table A.7 Robustness of import intensity-financial constraint interaction to alternative constraint measures.

This table examines the robustness of the financial constraints mechanism to alternative constraint specifications using the $[0, 2]$ event window. The dependent variable is cumulative abnormal return (CAR) at window [0,2]. Column (1) uses the composite financial constraint index from Table 8. This index is a composite measure combining standardized leverage (debt/assets), cash ratio (cash/assets), ROA (net income/assets), and log assets, with higher values indicating greater constraints. Columns (2)-(4) replace the composite index with individual constraint proxies: small firm indicator, low cash indicator, and high leverage indicator, respectively. Standard errors are clustered at the industry level to account for the industry-level measurement of import intensity. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels.

Variables	**(1)** **FC Index**	**(2)** **Size Only**	**(3)** **Cash Only**	**(4)** **Leverage Only**
Import Intensity	0.251*** (3.89)	0.273*** (3.75)	0.259*** (4.25)	0.246*** (3.81)
FC Index (standardized)	0.001 (1.01)			
Import Intensity × FC Index	-0.126** (2.46)			
Small Firm		0.004 (0.79)		
Import Intensity × Small Firm		0.077 (1.23)		
Low Cash			-0.005 (-0.83)	
Import Intensity × Low Cash			-0.081 (-0.96)	
High Leverage				-0.009 (-1.14)
Import Intensity × High Leverage				-0.033 (-0.79)
Log(Assets)	-0.008*** (-3.56)	-0.002 (-0.85)	-0.006*** (-4.17)	-0.005*** (-3.78)
Constant	0.090** (2.05)	-0.021 (-0.98)	0.057 (1.03)	0.046 (1.42)
Observations	500	500	500	500
R-squared	0.148	0.090	0.096	0.091

Table A.8 Two-way portfolio sorts by firm size and import intensity.

This table presents cumulative abnormal return (CAR) for all S&P 500 firms from independent two-way portfolio sorts based on firm size and import intensity following President Trump's tariff announcement on April 2, 2025. Firms are independently sorted into terciles by market capitalization (large, medium, and small) and by import intensity (low, medium, and high), creating nine portfolios. Panel A reports mean CAR for each of the nine portfolios. Panel B reports the difference in returns between High import and Low import firms within each size category, testing whether import intensity effects vary by firm size. The *t*-statistics in parentheses test whether each difference is significantly different from zero. CARs are calculated using the market model with parameters estimated over a 250-trading-day window ending 10 days before the event. All values are in decimal form. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Mean CAR by size and import intensity

Portfolio	Mean CAR over event window						
	$[-3, 3]$	$[-2, 2]$	$[-1, 1]$	$[-3, -2]$	$[0, 1]$	$[0, 2]$	$[0, 3]$
Large Firms:							
Low Import (N=60)	-0.043	-0.038	-0.016	0.002	-0.015	-0.042	-0.044
Medium Import (N=75)	-0.026	-0.017	-0.003	0.003	0.001	-0.020	-0.026
High Import (N=31)	0.033	0.015	0.006	-0.002	0.006	0.021	0.035
Medium Firms:							
Low Import (N=60)	-0.052	-0.044	-0.015	0.011	-0.016	-0.052	-0.063
Medium Import (N=77)	-0.020	-0.004	-0.002	-0.002	-0.001	-0.006	-0.016
High Import (N=30)	-0.009	-0.021	-0.018	-0.006	-0.018	-0.016	-0.004
Small Firms:							
Low Import (N=60)	-0.049	-0.040	-0.021	0.013	-0.016	-0.044	-0.058
Medium Import (N=77)	-0.022	-0.008	-0.014	-0.001	-0.012	-0.008	-0.018
High Import (N=30)	-0.027	-0.027	-0.019	-0.004	-0.019	-0.026	-0.023

Panel B: Import intensity effect within each size category

Large Firms	0.076***	0.053***	0.022*	-0.004	0.021**	0.063***	0.079***
(High - Low)	(3.89)	(3.24)	(1.73)	(-0.95)	(2.08)	(4.01)	(4.58)
Medium Firms	0.043**	0.023	-0.003	-0.017***	-0.002	0.036**	0.059***
(High - Low)	(2.15)	(1.28)	(-0.21)	(-3.45)	(-0.18)	(2.12)	(3.24)
Small Firms	0.022	0.013	0.002	-0.017***	-0.003	0.018	0.035*
(High - Low)	(1.08)	(0.71)	(0.13)	(-3.12)	(-0.28)	(0.98)	(1.79)

Table A.9 Export intensity and stock returns.

This table examines export intensity as an alternative measure of trade exposure. Export intensity is calculated as exports as a percentage of sales from firms' 10-K filings. Panel A presents portfolio sorts where firms are grouped into terciles and quintiles. Differences test whether high export-intensity firms generated different returns than low export-intensity firms. Panel B reports cross-sectional regressions of CAR on export intensity controlling for log assets, cash ratio, and leverage with robust standard errors. Panel C tests interactions between export intensity and firm characteristics. t-statistics in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	Cumulative Abnormal Return (CAR)				
	$[-3,3]$	$[-2,2]$	$[-1,1]$	$[0,2]$	$[0,3]$
Panel A: Portfolio Sorts by Export Intensity					
Tercile portfolio analysis:					
Low Export Tercile (N=196)	−0.045	−0.037	−0.013	−0.044	−0.055
Medium Export Tercile (N=159)	−0.026	−0.012	−0.010	−0.011	−0.020
High Export Tercile (N=145)	−0.003	−0.007	−0.009	−0.005	−0.000
Difference (High – Low)	0.042***	0.030**	0.004***	0.039***	0.054***
	(2.85)	(2.62)	(3.25)	(2.90)	(2.75)
Quantile portfolio analysis:					
Q1 (Lowest Export, N=135)	−0.041	−0.032	−0.011	−0.037	−0.048
Q2 (N=110)	−0.036	−0.019	−0.015	−0.029	−0.041
Q3 (N=86)	−0.028	−0.023	−0.007	−0.017	−0.020
Q4 (N=101)	−0.030	−0.018	−0.011	−0.022	−0.030
Q5 (Highest Export, N=68)	0.022	0.001	−0.007	0.009	0.027
Difference (Q5 – Q1)	0.063***	0.033**	0.004***	0.046***	0.075***
	(2.68)	(2.48)	(3.28)	(3.35)	(2.90)
Panel B: Cross-Sectional Regressions					
Export Intensity	0.084***	0.031*	−0.005	0.065***	0.126***
	(3.39)	(1.74)	(−0.36)	(3.29)	(5.54)
Log Assets	−0.003**	−0.006***	−0.003**	−0.005**	−0.002***
	(−2.59)	(−3.11)	(−1.96)	(−2.42)	(−2.78)
Cash Ratio	0.102***	0.075***	0.029**	0.089***	0.124***
	(4.44)	(3.98)	(2.00)	(4.57)	(5.46)
Leverage	−0.012	−0.001	0.008	−0.008	−0.018*
	(−1.17)	(−0.15)	(1.32)	(−0.90)	(−1.72)
R^2	0.118	0.087	0.023	0.124	0.193
Panel C: Interaction with Firm Characteristics					
Export × High ROA:					
Export Intensity	0.059**	0.023	−0.017	0.061***	0.120***
	(2.25)	(1.05)	(−0.99)	(2.83)	(4.83)
High ROA	−0.008	0.020	0.002	0.012	0.003
	(−0.58)	(1.61)	(0.22)	(0.95)	(0.20)
Export × High ROA	0.144**	0.035	0.038	0.052	0.099*
	(2.46)	(0.76)	(1.18)	(1.12)	(1.83)
R^2	0.120	0.107	0.030	0.119	0.163
Export × FC Index:					
Export Intensity	0.080***	0.023	−0.004	0.062***	0.123***
	(3.18)	(1.12)	(−0.29)	(2.99)	(5.24)
FC Index	0.001	−0.004	0.007**	−0.003	−0.008
	(0.13)	(−0.75)	(1.99)	(−0.58)	(−1.52)
Export × FC Index	−0.072***	−0.039***	−0.044***	−0.045***	−0.044**
	(−3.88)	(−2.61)	(−3.27)	(−2.95)	(−2.48)
R^2	0.153	0.113	0.040	0.143	0.204

Table A.10 Overall and industry-based average abnormal return (AAR) in the extended post-announcement period.

This table reports the average daily abnormal return (AAR) for all 500 stocks in the S&P 500 Index over each day in the medium-term post-event window (days +4 to +9). Alongside, industry-specific AAR for sample stocks across 11 GICS sectors, formed based on SIC classification, are reported. AAR is expressed in percentage (%). Statistical significance is tested using BMP and Wilcoxon signed-rank tests. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	+4	+5	+6	+7	+8	+9
Overall Market						
AAR	-0.82	1.33	-0.87	0.23	0.69	-0.18
BMP	-9.37***	12.30***	-7.43***	4.79***	13.56***	-4.21***
WRank	-8.18***	9.89***	-6.33***	3.85***	10.76***	-3.42***
Obs	500	500	500	500	500	500
Communication Services						
AAR	-0.48	1.54	-0.76	-0.48	0.27	0.77
BMP	-1.24	2.77***	-1.37	-0.85	1.22	2.61***
WRank	-1.61	2.37**	-1.19	-1.22	1.67*	2.52**
Obs	23	23	23	23	23	23
Consumer Discretionary						
AAR	-1.18	1.32	-0.87	-0.69	0.06	-0.42
BMP	-3.61***	3.06***	-1.28	-2.50**	0.75	-2.68***
WRank	-3.34***	3.01***	-1.64	-2.25**	0.21	-2.34**
Obs	51	51	51	51	51	51
Consumer Staples						
AAR	-2.04	2.64	0.14	1.14	1.36	-1.17
BMP	-9.32***	7.39***	0.87	6.24***	10.54***	-6.83***
WRank	-5.21***	4.44***	0.49	4.68***	5.27***	-4.72***
Obs	38	38	38	38	38	38
Energy						
AAR	-1.90	3.68	-4.58	1.50	-0.09	0.10
BMP	-4.96***	4.08***	-7.60***	5.01***	-0.63	0.60
WRank	-3.59***	3.07***	-4.14***	3.68***	-0.67	0.27
Obs	23	23	23	23	23	23
Financials						
AAR	0.29	1.12	-0.82	-0.11	0.71	0.29
BMP	2.04**	5.91***	-4.22***	-0.07	6.69***	1.57
WRank	2.36**	4.62***	-3.96***	-0.59	5.20***	2.08**
Obs	73	73	73	73	73	73
Health Care						
AAR	-1.53	1.16	-2.15	0.77	1.20	-1.04
BMP	-5.01***	4.58***	-5.19***	4.82***	6.14***	-6.77***
WRank	-4.62***	3.70***	-4.54***	4.07***	4.76***	-5.09***
Obs	60	60	60	60	60	60
Industrials						
AAR	-0.13	1.36	-0.11	0.37	0.34	-0.39
BMP	-0.72	4.21***	-0.11	2.42**	3.60***	-4.50***
WRank	-0.51	3.63***	0.31	1.82*	3.54***	-3.83***
Obs	76	76	76	76	76	76
Information Technology						
AAR	-0.34	-0.19	-0.48	-0.92	0.21	0.70
BMP	-1.56	0.86	-2.15**	-3.29***	1.72*	4.28***
WRank	-0.43	-0.40	-1.10	-3.27***	0.92	4.27***
Obs	69	69	69	69	69	69
Materials						
AAR	-2.46	2.67	-1.04	2.01	0.68	-1.12
BMP	-5.44***	3.63***	-1.84*	7.01***	3.77***	-3.99***
WRank	-3.65***	3.19***	-1.60	4.37***	2.92***	-3.40***
Obs	25	25	25	25	25	25
Real Estate						
AAR	-1.45	1.28	-0.78	0.26	1.87	0.16
BMP	-6.41***	4.12***	-3.51***	0.97	9.34***	1.15
WRank	-4.33***	3.16***	-3.14***	0.76	4.82***	1.72*
Obs	31	31	31	31	31	31
Utilities						
AAR	-0.21	1.02	0.24	0.73	1.49	-0.03
BMP	-1.79*	3.84***	1.71*	5.49***	9.44***	-1.21
WRank	-1.57	3.10***	1.88*	2.90***	4.12***	-0.59
Obs	31	31	31	31	31	31

Table A.11 Overall and industry-based cumulative abnormal return (CAR) over extended event windows.

This table reports the average cumulative abnormal return (CAR) for all 500 stocks in the S&P 500 Index over medium-term event windows extending beyond the immediate event period. Alongside, industry-specific CAR for sample stocks across 11 GICS sectors, formed based on SIC classification, are reported. CAR is expressed in percentage (%). Statistical significance is tested using BMP and Wilcoxon signed-rank tests. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$[0, 5]$	$[0, 9]$	$[1, 5]$	$[1, 9]$	$[4, 9]$
Overall Market					
CAR	-2.23	-2.37	-2.64	-2.78	0.38
BMP	-13.04***	-10.67***	-15.30***	-12.08***	4.48***
WRank	-9.58***	-8.67***	-11.26***	-9.95***	2.98***
Obs	500	500	500	500	500
Communication Services					
CAR	-1.86	-2.07	-1.94	-2.15	0.85
BMP	-1.91*	-1.45	-1.76*	-1.31	1.80*
WRank	-1.92*	-1.52	-1.79*	-1.28	1.22
Obs	23	23	23	23	23
Consumer Discretionary					
CAR	-0.15	-2.07	-1.14	-3.06	-1.77
BMP	-0.70	-2.24**	-2.05**	-3.41***	-2.54**
WRank	-0.46	-2.45**	-1.57	-3.52***	-2.66***
Obs	51	51	51	51	51
Consumer Staples					
CAR	-2.85	-1.39	-2.68	-1.23	2.06
BMP	-5.55***	-2.60***	-5.63***	-2.13**	4.93***
WRank	-4.04***	-2.52**	-4.18***	-2.24**	3.55***
Obs	38	38	38	38	38
Energy					
CAR	-10.58	-13.66	-10.71	-13.78	-1.29
BMP	-12.94***	-9.60***	-14.25***	-10.30***	-2.59***
WRank	-4.20***	-4.20***	-4.20***	-4.20***	-2.62***
Obs	23	23	23	23	23
Financials					
CAR	-3.47	-3.40	-3.99	-3.91	1.49
BMP	-10.05***	-9.59***	-12.94***	-10.89***	4.60***
WRank	-6.55***	-6.37***	-7.20***	-6.74***	3.70***
Obs	73	73	73	73	73
Health Care					
CAR	-2.02	-3.25	-2.51	-3.73	-1.59
BMP	-3.78***	-4.41***	-4.68***	-5.08***	-2.75***
WRank	-3.22***	-3.45***	-3.83***	-3.90***	-2.55**
Obs	60	60	60	60	60
Industrials					
CAR	-1.18	-0.96	-1.82	-1.60	1.44
BMP	-3.40***	-2.11**	-4.94***	-3.13***	3.43***
WRank	-2.74***	-1.61	-3.85***	-2.50**	2.55**
Obs	76	76	76	76	76
Information Technology					
CAR	1.98	1.49	1.79	1.29	-1.02
BMP	1.15	0.24	0.91	0.03	-1.42
WRank	2.31**	1.22	2.04**	1.00	-1.40
Obs	69	69	69	69	69
Materials					
CAR	-4.69	-4.16	-5.04	-4.50	0.74
BMP	-4.72***	-2.91***	-5.31***	-3.17***	1.29
WRank	-3.62***	-2.68***	-3.89***	-2.65***	1.04
Obs	25	25	25	25	25
Real Estate					
CAR	-4.92	-3.41	-5.20	-3.69	1.34
BMP	-8.10***	-5.13***	-8.91***	-5.33***	3.36***
WRank	-4.62***	-3.82***	-4.62***	-3.84***	3.16***
Obs	31	31	31	31	31
Utilities					
CAR	-3.75	-1.31	-4.10	-1.67	3.24
BMP	-7.67***	-3.18***	-8.78***	-3.70***	8.41***
WRank	-3.88***	-2.27**	-4.17***	-2.86***	3.74***
Obs	31	31	31	31	31

Table A.12 Overall and industry-based average abnormal return (AAR) around the event days using Fama-French five-factor model.

This table reports the average daily abnormal return (AAR), calculated using the Fama-French five-factor model, for all 500 stocks in the S&P 500 Index over each day in the event window. Alongside, industry-specific AAR for sample stocks across 11 GICS sectors, formed based on SIC classification, are reported. AAR is expressed in percentage (%). Abnormal returns are computed by adjusting for market, size, value, profitability, and investment factors. Statistical significance is tested using BMP and Wilcoxon signed-rank tests. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Sector	−3	−2	−1	0	+1	+2	+3
Overall Market							
AAR	-0.12	0.50	-0.10	0.22	-0.54	-1.54	-0.37
BMP	-2.40**	11.69***	-3.06***	3.75***	-2.69***	-12.38***	-7.04***
WRank	-2.25**	9.63***	-1.25	4.33***	-2.13**	-9.78***	-5.48***
Obs	500	500	500	500	500	500	500
Communication Services							
AAR	-0.78	1.29	-0.70	-0.12	-0.45	-1.66	-0.33
BMP	-3.14***	3.32***	-2.10**	-0.82	-0.64	-2.62***	-1.37
WRank	-2.80***	2.16**	-1.49	-0.58	0.27	-2.31**	-1.00
Obs	23	23	23	23	23	23	23
Consumer Discretionary							
AAR	-1.13	0.45	0.42	0.68	-1.61	1.55	-1.29
BMP	-4.58***	2.67***	2.48**	3.17***	-1.71*	2.94***	-4.90***
WRank	-4.36***	2.22**	2.07**	3.28***	-1.79*	3.10***	-4.04***
Obs	51	51	51	51	51	51	51
Consumer Staples							
AAR	-0.24	0.59	-0.01	-0.05	1.95	-2.81	-0.83
BMP	-1.38	3.67***	-0.45	-1.21	4.59***	-7.73***	-3.95***
WRank	-1.11	3.04***	-0.53	-0.73	3.56***	-4.47***	-3.26***
Obs	38	38	38	38	38	38	38
Energy							
AAR	0.63	0.30	0.39	0.08	-4.36	-5.76	0.43
BMP	3.50***	2.26**	3.56***	0.20	-6.49***	-14.04***	0.37
WRank	2.98***	2.22**	3.28***	0.55	-3.92***	-4.20***	0.97
Obs	23	23	23	23	23	23	23
Financials							
AAR	-0.23	0.79	-0.28	0.24	-0.79	-1.03	-0.59
BMP	-2.76***	7.20***	-3.68***	2.42**	-2.72***	-2.97***	-2.31**
WRank	-3.52***	5.97***	-3.03***	2.31**	-2.31**	-3.05***	-2.39**
Obs	73	73	73	73	73	73	73
Health Care							
AAR	0.11	0.58	-1.29	0.27	0.96	-2.89	-0.12
BMP	1.21	4.81***	-5.55***	1.96*	2.86***	-8.98***	-1.14
WRank	1.02	4.54***	-6.10***	2.23**	2.30**	-5.85***	-0.88
Obs	60	60	60	60	60	60	60
Industrials							
AAR	-0.43	0.40	0.18	0.34	-0.86	-1.19	-0.29
BMP	-4.42***	4.54***	2.03**	2.62***	-2.10**	-4.23***	-2.25**
WRank	-4.06***	3.55***	3.27***	3.34***	-1.97**	-3.50***	-1.99**
Obs	76	76	76	76	76	76	76
Information Technology							
AAR	0.07	-0.26	0.16	0.07	-1.20	0.24	1.58
BMP	-0.78	-1.09	0.60	-0.05	-2.57**	-0.84	3.91***
WRank	0.10	-1.93*	1.16	0.18	-2.27**	0.34	3.92***
Obs	69	69	69	69	69	69	69
Materials							
AAR	-0.60	0.64	0.16	0.14	-0.67	-3.22	-0.72
BMP	-3.79***	3.45***	1.27	1.19	-0.84	-4.51***	-2.77***
WRank	-3.22***	2.76***	0.96	0.85	-0.79	-3.48***	-1.92*
Obs	25	25	25	25	25	25	25
Real Estate							
AAR	0.91	0.63	-0.15	0.05	-0.57	-2.15	-1.97
BMP	6.46***	3.12***	-1.45	0.42	-1.49	-5.63***	-7.46***
WRank	4.27***	3.10***	-1.43	0.12	-1.61	-3.94***	-4.23***
Obs	31	31	31	31	31	31	31
Utilities							
AAR	1.10	0.96	0.38	0.35	0.94	-3.31	-1.54
BMP	9.11***	6.76***	1.57	1.18	4.43***	-11.39***	-6.52***
WRank	4.84***	3.92***	1.45	1.14	2.59***	-4.82***	-3.12***
Obs	31	31	31	31	31	31	31

Table A.13 Overall and industry-based cumulative abnormal return (CAR) over the event windows using Fama-French five-factor model.

This table reports the average cumulative abnormal return (CAR), calculated using the Fama-French five-factor model, for all 500 stocks in the S&P 500 Index over each day in the event window. Alongside, industry-specific CAR for sample stocks across 11 GICS sectors, formed based on SIC classification, are reported. CAR is expressed in percentage (%). Abnormal returns are computed by adjusting for market, size, value, profitability, and investment factors. Statistical significance is tested using BMP and Wilcoxon signed-rank tests. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Sector	$[-3,3]$	$[-3,2]$	$[-3,1]$	$[-2,2]$	$[-1,1]$	$[-3,0]$	$[-3,-1]$	$[-3,-2]$	$[0,1]$	$[0,2]$	$[0,3]$
Overall Market											
CAR	-1.94	-1.57	-0.03	-1.45	-0.41	0.51	0.29	0.38	-0.32	-1.86	-2.23
BMP	-10.71***	-8.10***	-0.55	-7.76***	-2.61***	5.42***	4.02***	6.53***	-1.68*	-10.66***	-12.65***
WRank	-8.86***	-7.21***	-0.70	-6.88***	-1.81*	5.55***	4.33***	5.60***	-1.00	-9.15***	-9.96***
Obs	500	500	500	500	500	500	500	500	500	500	500
Communication Services											
CAR	-2.75	-2.42	-0.76	-1.64	-1.27	-0.31	-0.19	0.51	-0.57	-2.23	-2.56
BMP	-3.04***	-2.70***	-1.00	-1.96*	-1.74*	-0.40	-0.04	1.30	-1.12	-3.12***	-3.08***
WRank	-2.80***	-2.71***	-0.36	-2.01**	-0.33	-0.91	-0.49	0.76	-0.09	-2.74***	-2.46**
Obs	23	23	23	23	23	23	23	23	23	23	23
Consumer Discretionary											
CAR	-0.92	0.37	-1.18	1.50	-0.51	0.43	-0.25	-0.68	-0.93	0.62	-0.66
BMP	-1.01	0.87	-0.83	2.43**	-0.23	0.87	-0.48	-1.51	-0.78	1.28	-0.84
WRank	-0.97	0.58	-1.07	1.82*	-0.40	1.12	0.07	-1.65*	-0.98	1.06	-0.66
Obs	51	51	51	51	51	51	51	51	51	51	51
Consumer Staples											
CAR	-1.41	-0.58	2.23	-0.34	1.88	0.28	0.34	0.35	1.90	-0.92	-1.75
BMP	-2.89***	-1.20	4.53***	-0.95	4.00***	0.54	1.81*	2.25**	4.38***	-1.97**	-3.59***
WRank	-2.75***	-1.89*	3.23***	-1.56	3.13***	0.91	1.78*	1.52	3.52***	-2.43**	-2.99***
Obs	38	38	38	38	38	38	38	38	38	38	38
Energy											
CAR	-8.29	-8.72	-2.96	-9.34	-3.89	1.40	1.32	0.93	-4.28	-10.04	-9.61
BMP	-7.76***	-9.53***	-3.42***	-11.61***	-5.43***	4.09***	5.09***	4.50***	-6.37***	-12.93***	-10.38***
WRank	-3.95***	-4.17***	-2.74***	-4.17***	-3.68***	3.19***	3.59***	3.19***	-3.83***	-4.20***	-4.20***
Obs	23	23	23	23	23	23	23	23	23	23	23
Financials											
CAR	-1.89	-1.30	-0.27	-1.07	-0.83	0.51	0.28	0.56	-0.55	-1.58	-2.16
BMP	-4.68***	-4.44***	-1.29	-3.81***	-3.21***	2.17**	1.05	3.19***	-2.25**	-5.74***	-5.38***
WRank	-4.27***	-4.25***	-1.32	-3.69***	-2.56**	2.25**	1.01	2.96***	-1.81*	-4.64***	-4.43***
Obs	73	73	73	73	73	73	73	73	73	73	73
Health Care											
CAR	-2.37	-2.25	0.64	-2.37	-0.05	-0.32	-0.60	0.69	1.23	-1.66	-1.78
BMP	-3.91***	-3.67***	1.49	-3.96***	-0.17	-1.12	-1.97**	4.41***	3.33***	-3.21***	-3.56***
WRank	-3.41***	-3.22***	1.13	-3.39***	-0.37	-0.33	-1.24	4.17***	3.02***	-2.86***	-2.83***
Obs	60	60	60	60	60	60	60	60	60	60	60
Industrials											
CAR	-1.84	-1.55	-0.37	-1.13	-0.34	0.49	0.15	-0.03	-0.52	-1.71	-1.99
BMP	-3.72***	-3.11***	-0.50	-2.31**	-0.61	2.26**	1.01	0.02	-1.21	-4.03***	-4.47***
WRank	-3.41***	-2.98***	-0.42	-2.17**	-0.26	2.23**	1.43	-0.26	-1.07	-3.64***	-3.80***
Obs	76	76	76	76	76	76	76	76	76	76	76
Information Technology											
CAR	0.67	-0.90	-1.15	-0.98	-0.96	0.05	-0.03	-0.19	-1.12	-0.88	0.70
BMP	-1.01	-2.67***	-2.68***	-2.74***	-2.43**	-0.83	-0.83	-1.35	-2.66***	-2.50**	-0.73
WRank	0.33	-1.36	-1.82*	-1.58	-1.82*	-0.40	-1.01	-1.80*	-2.15**	-1.49	0.46
Obs	69	69	69	69	69	69	69	69	69	69	69
Materials											
CAR	-4.28	-3.56	-0.33	-2.96	-0.37	0.34	0.20	0.04	-0.53	-3.76	-4.48
BMP	-3.03***	-2.23**	-0.01	-1.95*	-0.30	1.81*	1.25	0.85	-0.61	-2.91***	-3.70***
WRank	-3.08***	-2.49**	-0.17	-2.30**	-0.26	1.06	0.90	0.87	-0.44	-3.05***	-3.32***
Obs	25	25	25	25	25	25	25	25	25	25	25
Real Estate											
CAR	-3.26	-1.29	0.86	-2.19	-0.67	1.43	1.38	1.53	-0.52	-2.67	-4.64
BMP	-5.83***	-2.87***	1.62	-4.32***	-2.04**	6.02***	5.91***	7.10***	-1.68*	-6.67***	-8.78***
WRank	-4.06***	-2.33**	1.49	-3.35***	-2.27**	4.15***	4.08***	4.45***	-1.94*	-4.29***	-4.66***
Obs	31	31	31	31	31	31	31	31	31	31	31
Utilities											
CAR	-1.13	0.41	3.72	-0.69	1.66	2.78	2.43	2.05	1.28	-2.03	-3.56
BMP	-3.18***	1.47	11.40***	-1.68*	8.39***	12.51***	13.67***	10.64***	6.25***	-6.00***	-8.30***
WRank	-2.18**	1.12	4.82***	-1.61	4.78***	4.86***	4.86***	4.76***	3.74***	-4.33***	-4.49***
Obs	31	31	31	31	31	31	31	31	31	31	31

Table A.14 Overall and industry-based average abnormal return (AAR) around the "March 2018 China" tariff announcement.

This table reports the average daily abnormal return (AAR) for 475 stocks in the S&P 500 Index over each day in the event window surrounding the March 23, 2018 tariff announcement. Alongside, industry-specific AAR for sample stocks across 11 GICS sectors, formed based on SIC classification, are reported. AAR is expressed in percentage (%). Statistical significance is tested using BMP and Wilcoxon signed-rank tests. Statistical significance: ***, **, * indicate 1%, 5% and 10% levels.

	−3	−2	−1	0	+1	+2	+3
Overall Market							
AAR	0.05	0.12	0.05	-0.01	-0.18	0.32	0.03
BMP	1.31	0.96	0.05	-3.15***	-2.66***	6.23***	1.15
WRank	2.18**	1.23	1.62	-4.22***	-2.68***	5.60***	0.38
Obs	475	475	475	475	475	475	475
Communication Services							
AAR	-0.78	-0.08	0.39	0.22	-0.29	-0.28	-0.22
BMP	-3.06***	-0.07	2.47**	0.25	-1.42	-0.60	-0.10
WRank	-2.24**	-0.16	2.21**	1.09	-0.78	-0.64	-0.33
Obs	23	23	23	23	23	23	23
Consumer Discretionary							
AAR	0.24	0.02	-0.01	0.14	-0.07	0.40	-0.07
BMP	1.89*	0.23	-0.12	0.55	-0.35	2.39**	-0.22
WRank	1.49	0.41	-0.46	1.03	-0.82	2.65***	-0.40
Obs	62	62	62	62	62	62	62
Consumer Staples							
AAR	-0.22	-1.43	0.72	0.39	-0.03	-1.11	-0.98
BMP	-1.95*	-5.45***	4.86***	2.16**	-0.50	-5.67***	-4.46***
WRank	-1.56	-4.85***	4.04***	2.35**	-0.20	-4.35***	-3.70***
Obs	32	32	32	32	32	32	32
Energy							
AAR	0.69	2.81	0.51	1.09	-0.95	0.51	-1.58
BMP	2.09**	10.57***	2.15**	3.35***	-3.16***	2.65**	-6.43***
WRank	2.07**	3.98***	2.07**	2.66***	-2.73***	2.03**	-3.81***
Obs	23	23	23	23	23	23	23
Financials							
AAR	0.27	0.04	-0.84	-0.62	0.19	-0.14	0.33
BMP	3.31***	0.47	-8.76***	-5.73***	1.75*	-1.36	1.91*
WRank	2.96***	0.72	-6.21***	-4.91***	1.78*	-1.19	3.35***
Obs	64	64	64	64	64	64	64
Health Care							
AAR	-0.28	0.02	0.07	-0.07	-0.36	0.43	0.53
BMP	-1.07	1.30	0.51	-1.03	-2.31**	4.29***	2.35**
WRank	-0.08	0.70	1.59	-0.60	-1.68*	3.83***	1.97**
Obs	60	60	60	60	60	60	60
Industrials							
AAR	0.34	0.31	-0.54	0.34	-0.25	0.02	-0.11
BMP	3.44***	2.79***	-4.30***	1.88*	-1.90*	0.16	-1.22
WRank	3.45***	3.24***	-3.93***	1.08	-1.87*	0.21	-1.34
Obs	72	72	72	72	72	72	72
Information Technology							
AAR	0.35	0.17	0.30	-0.36	-0.08	-0.88	-1.15
BMP	1.68*	0.43	0.53	-2.50**	-0.40	-4.85***	-6.44***
WRank	3.65***	1.34	2.84***	-2.05**	-0.02	-4.55***	-5.87***
Obs	68	68	68	68	68	68	68
Materials							
AAR	-0.44	1.3	-0.84	0.75	-0.63	0.64	-1.12
BMP	-2.47**	5.44***	-2.60**	1.83*	-1.78*	3.78***	-4.41***
WRank	-2.07**	3.63***	-2.10**	1.76*	-2.03**	3.11***	-3.35***
Obs	28	28	28	28	28	28	28
Real Estate							
AAR	-0.23	-0.61	0.96	-0.24	-0.32	1.55	2.03
BMP	-1.54	-5.96***	4.09***	-1.45	-2.94***	7.65***	8.14***
WRank	-1.78*	-4.55***	3.61***	-1.59	-2.53**	4.47***	4.59***
Obs	29	29	29	29	29	29	29
Utilities							
AAR	-0.45	-0.03	1.48	-0.36	0.02	2.27	0.32
BMP	-4.19***	-0.38	13.05***	-3.64***	1.31	18.56***	2.07**
WRank	-3.43***	-0.57	4.70***	-2.74***	0.96	4.70***	2.41**
Obs	14	14	14	14	14	14	14

Table A.15 Overall and industry-based cumulative abnormal return (CAR) over the "March 2018 China" tariff announcement.

This table reports the average cumulative abnormal return (CAR) for 475 stocks in the S&P 500 Index over each day in the event window. Alongside, industry-specific CAR for sample stocks across 11 GICS sectors, formed based on SIC classification, are reported. CAR is expressed in percentage (%). Statistical significance is tested using BMP and Wilcoxon signed-rank tests. Statistical significance: ***, **, * indicate 1%, 5% and 10% levels.

	$[-3,3]$	$[-3,2]$	$[-3,1]$	$[-2,2]$	$[-1,1]$	$[-3,0]$	$[-3,-1]$	$[-3,-2]$	$[0,1]$	$[0,2]$	$[0,3]$
Overall Market											
CAR	0.38	0.35	0.08	0.23	-0.14	0.04	-0.01	-0.06	-0.19	0.13	0.16
BMP	2.82***	2.45**	0.40	1.78*	-0.87	0.39	-0.23	-0.69	-3.29***	1.99**	1.56
WRank	2.82***	2.85***	0.95	2.20**	-0.22	0.77	-0.17	0.71	-4.40***	2.32**	2.09**
Obs	475	475	475	475	475	475	475	475	475	475	475
Communication Services											
CAR	-1.04	-0.82	-0.43	-0.64	-0.04	-0.37	-0.46	-0.86	-0.07	-0.25	-0.67
BMP	-1.58	-1.55	-0.97	-1.22	-0.10	-0.97	-1.21	-2.17**	-0.16	-0.54	-1.32
WRank	-1.69*	-1.44	-0.82	-1.15	0.31	-0.93	-1.03	-1.87*	0.47	-0.16	-0.95
Obs	23	23	23	23	23	23	23	23	23	23	23
Consumer Discretionary											
CAR	0.65	0.72	0.32	0.48	0.06	0.39	0.25	0.26	0.07	0.47	0.40
BMP	1.42	1.82*	1.03	1.59	0.25	1.37	0.95	1.04	0.26	1.64	1.16
WRank	1.55	1.73*	0.98	1.54	0.36	1.37	0.93	1.07	0.41	1.57	1.18
Obs	62	62	62	62	62	62	62	62	62	62	62
Consumer Staples											
CAR	1.53	0.55	-0.58	0.76	-0.36	-0.79	-1.50	-1.72	0.37	1.48	2.46
BMP	3.51***	1.23	-1.17	1.73*	-0.84	-2.05**	-3.33***	-3.76***	1.01	3.38***	5.23***
WRank	3.65***	1.87*	-0.44	2.23**	-0.18	-1.12	-2.35**	-2.91***	1.21	3.28***	4.35***
Obs	32	32	32	32	32	32	32	32	32	32	32
Energy											
CAR	3.07	4.65	5.64	3.86	1.65	4.74	4.23	3.42	0.14	-0.44	-2.02
BMP	3.19***	4.93***	6.40***	4.57***	2.08**	6.39***	7.12***	6.56***	0.18	-0.52	-2.12**
WRank	2.59***	3.53***	3.91***	3.86***	1.78*	3.86***	3.86***	3.86***	0.47	-0.52	-2.07**
Obs	23	23	23	23	23	23	23	23	23	23	23
Financials											
CAR	-0.77	-1.10	-1.30	-0.87	-1.03	-0.49	0.35	0.31	-0.43	-0.57	-0.24
BMP	-2.69***	-4.70***	-5.83***	-4.16***	-5.17***	-2.31**	1.55	1.40	-2.05**	-2.65***	-1.08
WRank	-2.73***	-4.21***	-5.09***	-3.86***	-4.38***	-2.14**	1.11	1.02	-2.05**	-2.58***	-1.23
Obs	64	64	64	64	64	64	64	64	64	64	64
Health Care											
CAR	0.35	-0.18	-0.25	-0.21	-0.32	-0.32	-0.28	-0.30	-0.43	-0.11	0.42
BMP	0.43	-0.68	-1.03	-0.83	-1.38	-1.41	-1.26	-1.27	-2.00**	-0.44	1.36
WRank	1.04	-0.01	-0.28	-0.10	-0.44	-0.60	-0.52	-0.56	-1.25	0.12	1.66*
Obs	60	60	60	60	60	60	60	60	60	60	60
Industrials											
CAR	0.11	0.22	0.47	0.11	-0.19	0.15	0.81	0.35	-0.20	-0.23	-0.34
BMP	0.41	0.88	2.14**	0.51	-0.94	0.77	3.79***	1.70*	-1.06	-1.06	-1.57
WRank	0.70	0.98	1.94*	0.59	-0.63	0.84	3.24***	1.59	-0.85	-0.78	-1.24
Obs	72	72	72	72	72	72	72	72	72	72	72
Information Technology											
CAR	-1.66	-0.51	0.37	-0.86	-0.14	0.33	0.52	0.70	-0.44	-1.24	-2.39
BMP	-4.26***	-1.39	1.05	-2.58***	-0.49	1.32	2.00**	2.57***	-1.53	-3.92***	-6.82***
WRank	-4.21***	-0.99	0.98	-2.10**	-0.15	1.46	2.39**	2.61***	-0.87	-2.86***	-4.55***
Obs	68	68	68	68	68	68	68	68	68	68	68
Materials											
CAR	-0.31	0.82	1.46	1.25	0.91	0.54	-0.30	-1.74	0.12	1.39	0.27
BMP	-0.19	1.48	2.61***	2.42**	1.77*	1.20	-0.61	-3.23***	0.28	2.50**	0.47
WRank	-0.61	1.59	2.49**	2.28**	1.68*	1.06	-0.53	-2.63***	0.21	2.21**	0.32
Obs	28	28	28	28	28	28	28	28	28	28	28
Real Estate											
CAR	3.13	1.11	1.43	1.34	0.64	0.36	-0.60	-0.84	0.88	2.43	4.46
BMP	8.49***	3.14***	4.52***	3.94***	2.18**	1.30	-2.13**	-3.01***	3.13***	8.46***	13.30***
WRank	4.45***	2.22**	2.93***	2.60***	1.65*	1.01	-1.50	-2.29**	2.22**	4.55***	4.80***
Obs	29	29	29	29	29	29	29	29	29	29	29
Utilities											
CAR	3.26	2.94	1.46	2.78	1.11	0.67	-0.81	-0.84	-0.34	1.92	2.24
BMP	9.67***	8.86***	4.47***	8.47***	3.31***	2.05**	-2.45**	-2.53**	-1.04	5.87***	6.86***
WRank	4.64***	4.41***	2.94***	4.33***	2.03**	1.31	-1.41	-1.70*	-0.57	3.59***	4.12***
Obs	14	14	14	14	14	14	14	14	14	14	14