Trade Policy Shocks and Market Reactions: An Event Study with LLM-Derived Measures of USTR Tariff Announcements

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Abstract

This paper examines how United States trade policy shocks affect equity markets, specifically semiconductor-related firms, by studying reactions to U.S. Trade Representative (USTR) Section 301 tariff announcements. Focusing on Taiwan Semiconductor Manufacturing Corporation (TSMC) and related firms, we combine a standard event study framework with Large Language Model (LLM)-derived measures extracted from tariff policy texts. Using daily returns, we compute abnormal returns (ARs) and cumulative abnormal returns (CARs) around tariff notices, modifications, and exclusion announcements. To quantify the content of such documents, we employ an LLM to assign each announcement severity, surprise, direction, and rational classifications, transforming unstructured text into variables to be used in regression analysis. Our results show that relief announcements consistently generate positive ARs, while mixed and restrictive announcements produce weaker and ambiguous market responses. Information resolution dominates severity and surprise labels in explaining CARs, suggesting that markets may respond more strongly to changes in information uncertainty than to the magnitude of policy actions. While the LLM-derived measures do not outperform manual classifications, they improve explanatory power when used together. Overall, this paper explores the integration of Generative AI with the event study framework to enhance the study of trade policy shocks and market reactions, and provides a baseline for further research in the area.

1 Introduction

Context and Motivation

The global semiconductor industry sits at the intersection of politics, innovation, and economics. Taiwan Semiconductor Manufacturing Corporation (TSMC) is the exclusive firm, producing over half of the world's semiconductors. While U.S. trade policy does not directly impose tariffs on TSMC's exports, its production costs are affected through tariffs on input materials, notably silicon, chemicals, and semiconductor manufacturing equipment. Since 2018, the U.S. Trade Representative (USTR) has implemented and withdrawn tariff exclusions for semiconductor inputs under Section 301 trade actions. These policy changes can influence investor expectations, firm financing conditions, and ultimately TSMC's cost of equity.

Problem Statement

Despite extensive literature on the trade war's impact on prices and exports, little research isolates market effects on key supply-chain leaders like TSMC, who is responsible for the almost exclusive production of semiconductors. Because these tariffs target products, their effects propagate indirectly though the supply chain, altering not only production costs but also perceived risk rather than demand. This project studies the market impact of these announcements by examining abnormal returns around the release of USTR tariff exclusions, modifications, and notices of action.

Research Objective and Contributions

The goal of this project is to quantify how tariff announcements impact the performance of TSMC and comparable firms. Using an event study with abnormal returns (AR) and cumulative abnormal returns (CAR) regressions, we measure abnormal returns surrounding each announcement to capture market reactions. A key methodological contribution is the use of an LLM classification to extract measures from USTR policy texts, which include severity, surprise, direction, and rationale. These LLM-derived measures allow for the differentiation between types of policy implications and the testing of whether announcements explain variation in market reactions. Together, the event study and LLM outputs provide new insight into how trade policies affect equity performance in the semiconductor, energy, and broader technology sectors.

2 Literature

The semiconductor industry's historical dependence on globally controlled inputs makes it sensitive to policy implications such as tariffs and policy shocks (Nguyen, 2021; Flamm, 1993). Since 2018, USTR tariffs on silicon and other related inputs have introduced uncertainty in the market, affecting firms like TSMC through indirect input cost shocks (Xiong, 2025).

Theme 1: Trade Policy, Tariffs, & Semiconductor Industry

Foundational studies on international trade policy and the general semiconductor industry describe how competitiveness between firms is affected by strategic trade policies (Flamm, 1993), while more recent work highlights how tariff-induced input shocks influence global supply chains (Nguyen, 2021; Xiong, 2025). Together, these show that even firms that are not directly affected by tariffs such as TSMC suffer secondary consequences due to policy changes that target input materials.

Theme 2: Trade Policy Uncertainty & Financial Market Effects

Studies that use firm-level data find that trade protection reduces equity valuation, which in turn increases risk premia (Amiti et al., 2021; Bianconi et al., 2021; Yilmazkuday, 2025). Models incorporating macroeconomic variables support these findings, showing that as policy uncertainty increases, investment declines (Caldara et al., 2020). Additionally, heterogeneity across industries suggests that equity valuations are dependent on supply chain movements (Gallo & Cocozza, 2025), which justify the use of a comparative analysis between TSMC, smaller foundries, and non-semiconductor firms. Finally, recent market studies confirm that even during the U.S. and China trade war, economic and financial shocks are both quantifiable and measurable (Amiti et al., 2024).

Theme 3: Firm-Level Financial Analysis & AI Forecasting

Firm level financial analyses identify TSMC's sensitivity to global markets and input/production costs, where advances in AI forecasting demonstrate that large language models can identify signals from textual data such as policy announcements and earnings reports (Xu, 2025; Lopez-Lira, 2023). The success of the implementation of such models yields measurable improvements in the accuracy of equity prediction. The bridge between econometric analysis and AI modeling opens the door for future combined approaches to predictive financial frameworks.

Contribution & Entry Point

While existing literature establishes that tariffs influence stock returns and that AI models enhance forecasting accuracy, no existing studies directly integrate tariff shocks with equity estimation using event studies or generative AI models. This project attempts to add meaningful contributions by combining an event study design with AI methods, trained on USTR policy texts, to link policy changes with a predictive framework for TSMC and similar firms.

3 Data

3.1 USTR Policy Text Corpus & Event Label Construction

The policy text corpus contains Section 301 tariff documents issued by the USTR, which represents the source of trade policy actions that affect semiconductor firms. Each of the four lists within Section 301 is related to a trade action, and contains notice of actions, modifications, and exemptions. As shown in Table 1, relevant documents were hand selected and then automatically parsed via filename regex[1]. For each document, the text was extracted and mapped

[1] Document titles were constructed as "L{list_id}_{document_type}_{date}"

into a new dataset that included event date, tariff list, document type, clean text, rationale text, action type, and direction. Table 2 shows examples of the addition of action type and direction. Note that clean and rationale texts were omitted for the sake of space. Then, severity scores were manually calculated, depending on the relevance, document type, and content. Notice of actions were scored with a severity score of 3, modifications and semiconductor-related exclusions with a severity score of 2, and other exclusions with a score of 1. Additionally, a severity index is computed, which takes categorical labels and creates a numerical index, where lower values of the index correspond to less severe tariff actions, and vice versa for use in later regression models. This dataset was then combined with the methodological measures, as shown in Table 3, and with CAR windows and AR series and other measures in Table 4.

3.2 Firm Level Return Data & Ticker Universe

TSMC equity data, specifically daily closing prices and returns (computed as percent changes), and other related company equity data was obtained via the yfinance package from Yahoo Finance. The firm sample includes supply-chain firms, selected to capture the heterogeneous effects of semiconductor-related trade policy shocks. These companies include Apple, NVIDIA, AMD, Samsung, Google, Formosa Petrochemical Corporation, and United Renewable Energy Co Ltd, which were chosen due to their relevance to semiconductors, the technology industry, and their role in the supply chain. Companies were also grouped into four sectors: semiconductors, downstream technology, energy/chemicals, and renewables, for use in multiple regressions and the plotting of CARs by sector. Additionally, S&P 500 equity data is gathered and used as the baseline for market returns in the event study. Return estimations were calculated via percent changes in TSMC and S&P 500.

3.3 Estimation & Event Windows

Estimation and event windows allow expected and actual returns to be dependent on the time leading up to and after an event. Estimation windows are strictly pre-event, and used to estimate the expected returns from 120 to 20 days before the event. This window is intentionally separated from the event window to avoid contamination by event-related information. Thus, the event window is centered around the event date, five days before and after the event. This window is used to measure abnormal price responses that are attributed to the event.

3.4 Abnormal Returns & CARs

Using both the estimation and event windows and to capture market movements, cumulative abnormal returns and abnormal returns were calculated. The equations for these calculations are as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} \tag{a}$$

$R_{i,t}$ = return of firm i on day t

$R_{m,t}$ = market index return on day t

α_i, β_i = firm specific parameters estimated via OLS

$\epsilon_{i,t}$ = idiosyncratic return

$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t} \tag{b}$$

$$\hat{R}_{i,t} = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \tag{c}$$

$$CAR_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_{i,t} \tag{d}$$

τ_1, τ_2 define the start and end of the event window

Equation (a) represents the market model for expected returns, where returns for a certain firm and day are dependent on a constant, the market index return on that day, and some idiosyncratic return term. This model is estimated via OLS, where parameters α_i and β_i represent the coefficients for the intercept and market return, respectively. Equation (b) measures abnormal returns, where the ARs measure the portion of a firm's return that cannot be explained by general market movements. That is, the difference between the actual return and estimated return. Estimated return is modeled in Equation (c), where estimated market return is represented by the market index return. These ARs are computed for every day in the event window, for each firm. If ARs are greater than zero, that means the firm experiences outperformance. If ARs are less than zero, that means the firm is experiencing underperformance.

4 Methods

4.1 Event Study

Overview of the Event Study

As a standard method in finance and econometrics used to isolate the effects of identifiable events on market movements, the event study framework examines the short run stock market response to discrete trade policy announcements. The event study allows for the comparison of observed returns to a benchmark of expected returns surrounding an event. An assumption of the event study framework is that in an efficient financial market, new information affects asset prices, almost immediately. This causes the observation of abnormal returns to be interpreted as the market's assessment of the economic impact of an event.

Motivation for Use

An event study is well-suited for this research topic for three reasons. First, trade policy announcements are released at defined points in time, which allows for the labeling of event dates and the creation of a unique observation dataset. Second, these announcements always convey information about the strategic risks faced by firms, which allows stock returns to be a sufficient outcome or dependent variable for regression analysis. Lastly, by creating windows around events, the event study attempts to minimize exogenous factors unrelated to the specific policy action. Essentially, this framework enables the analysis of immediate market reactions in response to trade policy shocks.

Assumptions & Considerations

The first assumption of the event study approach is that markets must incorporate new information quickly, so that abnormal returns are concentrated within the predefined event window. Next, the event date must be correctly identified, assuming the listed date on each announcement is correct. Additionally, events should not coincide with other major firm or market level shocks. This is partially accounted for by clustering robust standard errors. Finally, the defined estimation window must provide an unbiased estimate of normal returns. That is, the definition of "normal" versus "abnormal" returns must be as optimal as possible.

4.2 LLM Classification

To quantify the qualitative component of trade policy announcements, we employ a LLM, specifically Ollama 3.2, to classify policy related documents according to their impact on semiconductor-related firms. This approach allows for the transformation of unstructured text to quantitative measures that are suitable for our event study analysis. The LLM operates on the cleaned text of policy documents which were compiled into a single CSV file. Each observation corresponds to a distinct policy event, and contains input text that is processed to remove formatting to ensure consistency. The prompt for the LLM is below:

> You are a financial policy analyst. Given the full text of a USTR Section 301 tariff-related document, classify its expected impact on semiconductor-related firms.

You MUST return a JSON object with exactly these keys:
- "severity": integer in {0,1,2,3} where, 0 = no meaningful impact on semiconductors, 1 = mild impact, 2 = moderate impact, and 3 = high / severe impact
- "surprise": float in [0,1] where higher = more surprising to markets
- "direction": one of {"tightening","relief","mixed","unknown"}
- "rationale": short natural-language explanation (2–3 sentences).

Return ONLY valid JSON. No extra commentary or text; just the JSON object.

This prompt transforms the policy language into structured measures which are analogous to the manual classification, while allowing for numeric classification. It requires the model to return a strictly formatted JSON file which contains four outputs: Severity, Surprise, Direction, and Rationale. Severity is an integer which captures the magnitude of the document's impact on semiconductor firms, where the greater the integer, the more meaningful the impact is. Surprise is a continuous number between zero and one which serves as a proxy for how "unexpected" the policy action is from a general market perspective. The closer the score is to one, the more surprising the implementation is. Direction is a categorical indicator that describes whether the policy represents trade tightening, relief, mixed effects, or an undetermined (unknown) direction. Finally, the Rationale is a short explanation which justifies the classification of the three labels. Note that each document is processed independently, with outputs extracted and set as new variables: severity_ollama, surprise_ollama, direction_ollama, and rationale_ollama. Table 5 shows the summary statistics of the measures obtained after Ollama classification. These outputs are then integrated into the event study as new components of regressions, using the LLM classifications as variables of interest.

4.3 Regression Models

To capture the effects on CARs that policy text labels have, seven different linear regression models were estimated. In these regressions, i denotes the firm, e the event, w the

CAR window, m a manual label, and l an LLM label. Because firms share event dates, observations are thus not i.i.d. Therefore, clustering by event date is needed. So, to achieve cluster-robust standard errors, we get:

$$\epsilon_{i,e} \sim cluster(e)$$

This ensures that standard errors are clustered at the event-date level to adjust for the correlation across firms that react to the same tariff announcement. First, a baseline regression using manual severity and direction labels. This initial specification provides a baseline for comparison with the LLM labels and further regression models. In this model, CARs of a certain firm, event, and window are dependent on the manual severity score, manual direction label, and any other factors not incorporated in the two predictors.

$$CAR_{i,e,w} = \beta_0 + \beta_1 Severity_{e,m} + \beta_2 Direction_{e,m} + \epsilon_{i,e} \quad (1)$$

The following regression is similar to the first one, though instead with LLM-derived Severity and Direction labels and the addition of the LLM-derived Surprise label:

$$CAR_{i,e,w} = \beta_0 + \beta_1 Severity_{e,l} + \beta_2 Surprise_{e,l} + \beta_3 Direction_{e,l} + \epsilon_{i,e} \quad (2)$$

Combining the linear terms from Regressions 1 and 2, we achieve Regression 3. This model jointly captures market-level and event-level policy characteristics, which allows market reactions to vary with both the magnitude of the policy and its unexpected component.

$$CAR_{i,e,w} = \beta_0 + \beta_1 Severity_{e,m} + \beta_2 Direction_{e,m} + \beta_3 Severity_{e,l}$$
$$+ \beta_4 Surprise + \beta_5 Direction_{e,l} + \epsilon_{i,e} \quad (3)$$

To reduce dimensionality and capture overall policy intensity as a numeric factor, the remaining regressions utilize the Severity Index in place of the Severity label. This numerical indexing is used in hopes of better capturing the quantitative effects of policies on CARs.

Regression 4 models TSMC CARs only, using the Severity Index and the Direction label. Regressions 5 and 6 are identical, but run over all firms. The two regressions were run separately, once in the same block as Regression 4 for direct comparison, and again as a standalone model.

$$CAR_{TSMC,e,w} = \beta_0 + \beta_1 Severity\ Index_e + \beta_2 Direction_e + \epsilon_{i,e} \quad (4)$$

$$CAR_{all,e,w} = \beta_0 + \beta_1 Severity\ Index_e + \beta_2 Direction_e + \epsilon_{i,e} \quad (5, 6)$$

Finally, sector fixed effects are included in the model for TSMC only to control for unobserved heterogeneity across sectors. These fixed effects absorb time-invariant characteristics that may be affecting TSMC CARs outside of policy actions.

$$CAR_{TSMC,e,w} = \beta_0 + \beta_1 Severity\ Index_e + \beta_2 Direction_e + Sector\ FE + \epsilon_{i,e} \quad (7)$$

5 Results

5.1 Abnormal Returns

Preliminary Analysis of CARs

In a preliminary exploration of the calculated cumulative abnormal returns, the distribution of TSMC CARs is positively skewed, indicating asymmetric market responses across policy events, as shown in Figure 1. The variation in CARs shows that some events generate large positive abnormal returns between 15 and 20 percent, while most lead to substantial declines up to negative 10 percent. This confirms that not all tariff announcements have the same impact, and justifies the classification of events by severity and surprise measures. There are huge differences between severity levels, as shown in Figure 2, where severity level 2 events correspond to positive CARs of about two percent, indicating that smaller magnitude tariff actions generate somewhat positive abnormal performances for TSMC. On the other hand, severity level 3 events yield negative CARs, suggesting that policies that are more impactful or that are more restrictive are perceived harsher by investors. This difference implies that market reactions are systematically related to the severity of tariff announcements and confirms the use of the severity index in our regression analysis. As for all events and firms from a general point of view, we identify the trend in CARs 10 days leading up to and after the event, as shown in Figure 3. The trend leading up to the event is relatively steady and slightly increasing, which is consistent with anticipatory positioning among investors, then dipping around the time of the event, only to grow rapidly afterwards up to 3.8 percent by day 10. The implication from this finding is that tariff announcements do not necessarily produce negative effects, but rather the resolution of uncertainty surrounding each policy often reassures investors. This aligns with the economic intuition that exclusion announcements and official notice of actions can be better than anticipation and uncertainty.

Short Run Analysis of ARs Around Events by Sector

Figure 4 displays the average abnormal return five days before and after events for all firms included in this paper. Leading up to the events, industries show slightly positive but somewhat declining ARs, consistent with anticipation effects or information leakage. When looking at TSMC individually and the semiconductor sector, in Figure 5 and Figure 6, the trends are somewhat identical to the average across all firms. However, other sectors experience very different pre-event trends. Figure 7 displays the ARs for the downstream technology sectors, where ARs initially decrease but spike right before the event, suggesting different anticipation effects for this sector only. After the event, ARs remain steady around zero for three days, only to spike up positively on day four and dip far below zero on day five. Figure 8 and Figure 9 show ARs for the energy/chemicals and renewables sector, where ARs actually dip negative leading up to the event. In the energy/chemicals sector, ARs remain negative for almost three days after the event, and rebound positively after day three. The renewables sector never fully recovers to positive ARs after five days after the event.

Together, these figures reveal heterogeneity in tariff sensitivity across sectors. The findings of TSMC demonstrate that TSMC's reaction is directionally aligned with both the broader semiconductor industry and the sample of firms used in this paper. These plots also establish the timing structure of market responses around events, validating our methodology and the selection of an event study.

5.2 Event Study Regressions

CAR Manual Model

In this model, we analyze how manual severity and direction labels affect CARs. Manual severity labels have a coefficient near zero and a statistically insignificant p-value, suggesting that the manual severity labels do not predict abnormal returns. The relief direction is positive and statistically significant, indicating that relief announcements generate positive CARs of about 1.5 percent. The mixed direction shows borderline significance, though insignificant, and the tightening direction is clearly insignificant, suggesting that the markets respond positively to identified relief actions. With no significance of manual severity labels, this model serves as a baseline for the following two models and justifies the use of an LLM labeler and a combined model.

CAR LLM Model

This model is identical to the previous baseline model, where the severity and direction labels were generated from the Ollama classification to obtain severity, surprise, high/severe impact, mixed, relief, tightening, and unknown labels. We find that across all variables, there was no statistical significance. That is, LLM-derived variables alone do not predict CARs, and highlights the need for a combined or more extensive model.

CAR Combined Model

The combined model is the addition of LLM-derived variables to the baseline manual model. We find that manual relief and mixed directions are statistically significant, with LLM-derived severity being borderline significant. All other variables are insignificant. From this combined model, we see that manual direction continues to be the strongest predictor. LLM severity among other LLM-derived measures begin to show meaningful impact, even if imprecise, when included in a combined model.

CAR Severity Index (TSMC Only)

This is the first model that exhibits high statistical significance, where relief and tightening directions possess both positive coefficients and statistical significance. The severity index, different from a manual/LLM label, is not significant in this model. For TSMC alone, we observe that relief and tightening actions both increase CARs. Relief actions being related to increasing CARs aligns with intuition, however tightening being correlated to increasing CARs is counterintuitive. Overall, this pattern is consistent with the thought that investors interpret clarity, regardless of the direction, as reducing uncertainty, therefore boosting CARs. Additionally, this reveals that policy directions may not matter as much for TSMC compared to the confirmation or resolution of information.

CAR Severity Index (All Firms)

When looking at all firms together in the same model as previously stated, we observe no significance among any of the variables, except the relief direction, similar to the baseline model.

The loss of significance among additional variables when drawing on the data of all firms together reinforces the identification of heterogeneity among different market sectors.

CAR Sector Fixed Effects

When incorporating sector fixed effects into the model, we continue to see the relief direction being statistically significant, with the addition of the semiconductor sector being borderline significant. Tariff relief continues to be directionally positive but weaker in significance, suggesting that the underlying effect is at the firm-level and not apparent across industries. That is, sector membership does not strongly predict CARs, which is consistent with the heterogeneity shown in the above sections and plots.

6 Discussion

Findings and Interpretations

We find that relief announcements consistently generate positive abnormal returns across model specifications and firm subsets. Mixed announcements produce negative and ambiguous market responses, which aligns with uncertainty effects. Neither manually labeled nor LLM-derived severity and surprise scores were statistically strong predictors of CARs. Therefore, market reactions appear to be driven more by the direction of the announcement and the certainty around events rather than the intensity of the policy action, and investors may interpret announcements in conjunction with information clarity/uncertainty surrounding events.

Evaluation of AI-Derived Labels

LLM labels were introduced to supplement manual assignments of measures of tariff texts by extracting latent information within each announcement. The foundational idea behind this decision is that policy documents contain signals such as tone and implications that LLMs would be able to possibly detect. We observed that LLM severity scores showed weak and noisy negative effects on CARs when included in certain regressions, LLM direction classifications did not outperform manual labels, and LLM surprise scores showed no relationship with CARs. This underperformance can be attributed to numerous reasons. 1) Policy texts may not be the true source of information backing investor decisions and expectations. That is, other sources such as news outlets or analyst findings could matter more to certain investors. 2) The number of events gathered in this paper is relatively small for LLM-based inference. 3) Policy text structure may not exhibit severity in the way we intend to use it in regression analysis, as policy writers often write with neutral and technical tones. For these reasons, there are further methodological limitations that arise with these models.

7 Limitations

Building on point 2) from above, there are certainly data limitations of this paper, including the limited number of tariff events reduces statistical power, the sensitivity of CARs to estimation windows in high frequency returns, and the differences between event dates and actual information arrival (and/or leaked information arrival). For the LLM specific limitations, there is no formal ground truth of "severity" and "surprise" labels, creating potential classification instability across the event samples, and ultimately leading to the misinterpretation of the language in tariff texts by the LLM. Lastly, the choice of using linear regression analysis may not capture other effects, including nonlinear effects that could be captured by other regression models. Omitted variable bias and multicollinearity are also factors that can cause unstable and misleading coefficient estimates. On the bright side, this paper can be used as a stepping stone for further methodological developments for analyzing policy implications using AI methods, highlighting the areas for further research and model development.

8 Directions for Future Work

The first step for the continued development of this project would be to enhance the text analysis pipeline, specifically using embeddings rather than categorical labels. This would allow for the building of continuous severity indices using cosine similarity, clustering or other embedding methods. Additionally, implementing fine-tuned models on trade policy specific corpora would allow for a more accurate classification of policy texts, such as clearly defining what “severity” means. Next, to improve the event study design, policy sources could be expanded to include press releases, news headlines, analyst reports, etc. The inclusion of announcements outside of the USTR would allow for the classification of leaked and surprise announcements, better capturing the anticipation effects that affect investor decisions. Expanding not only the text sample but the data sample by including more firms and building the ticker universe to add to extended regression models can increase statistical explanatory power. Lastly, an expansion in the financial framework could be beneficial to this research. Specifically, considering trading volume, volatility, and other important measures to better capture the effects that tariff shocks have on all aspects of the market. The subsequent LLM-based labels therefore may predict the market and its volatility better than simply looking at mean returns.

9 Conclusion

This paper aimed to explore how USTR tariff announcements affect equity markets, with a focus on TSMC and similar firms. Using a combined methodology of an event study and LLM-based text classification, regression analysis was compared between manual and generated labels, and the effect of these variables on cumulative abnormal returns as a measure of market responses. Relief announcements generate positive CARs across all models, while other directional labels did not produce significant results. Information clarity mattered more than severity and surprise scores, indicating that market reactions reacted more to uncertainty surrounding the event compared to the intensity of policy actions. From sector fixed effects, market reactions are heterogeneous across sectors, with TSMC following trends in the broader semiconductor industry. LLM-derived measures added value only when combined with manual labels, as LLM-only models failed to exhibit significance and explanatory power. The methodological contributions demonstrated the feasibility of using LLM-extracted policy features into standard financial event studies. Even though the findings were not statistically significant across the models, this study provides an empirical framework for further work in this methodology and research area.

Integrating Generative AI with traditional empirical finance is promising, though requires careful design, more comprehensive data, and domain-specific fine tuning. This paper provides a first step, not a definitive verdict, on LLM performance and equity data, and can inform future research on policy shocks, financial market, and ultimately AI-assisted econometric analysis.

10 References

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11 Appendix

11.1 Tables

Summary of Events Used in the Event Study (Top 10)

	event_id	file_name	list_id	doc_type	event_date
0	L1_noticeofaction_20180620	L1noticeofaction_20180620.pdf	1.000	noticeofaction	2018-06-20 00:00:00
1	L2_noticeofaction_20180816	L2noticeofaction_20180816.pdf	2.000	noticeofaction	2018-08-16 00:00:00
2	L3_noticeofaction_20180921	L3noticeofaction_20180921.pdf	3.000	noticeofaction	2018-09-21 00:00:00
3	L1_exclusions_20181228	L1exclusions_20181228.pdf	1.000	exclusions	2018-12-28 00:00:00
4	L1_exclusions_20190325	L1exclusions_20190325.pdf	1.000	exclusions	2019-03-25 00:00:00
5	L1_exclusions_20190418	L1exclusions_20190418.pdf	1.000	exclusions	2019-04-18 00:00:00
6	L3_modification_20190509	L3modification_20190509.pdf	3.000	modification	2019-05-09 00:00:00
7	L1_exclusions_20190514	L1exclusions_20190514.pdf	1.000	exclusions	2019-05-14 00:00:00
8	L1_exclusions_20190604	L1exclusions_20190604.pdf	1.000	exclusions	2019-06-04 00:00:00
9	L1_exclusions_20190709	L1exclusions_20190709.pdf	1.000	exclusions	2019-07-09 00:00:00

Table 1: Summary of events used in the event study

Summary of Events Used in the Event Study With Action Type and Direction (Top 10)

	event_id	file_name	list_id	doc_type	event_date	action_type	direction_guess
0	L1_noticeofaction_20180620	L1noticeofaction_20180620.pdf	1.000	noticeofaction	2018-06-20 00:00:00	imposition	tightening
1	L2_noticeofaction_20180816	L2noticeofaction_20180816.pdf	2.000	noticeofaction	2018-08-16 00:00:00	imposition	tightening
2	L3_noticeofaction_20180921	L3noticeofaction_20180921.pdf	3.000	noticeofaction	2018-09-21 00:00:00	imposition	tightening
3	L1_exclusions_20181228	L1exclusions_20181228.pdf	1.000	exclusions	2018-12-28 00:00:00	exclusions	relief
4	L1_exclusions_20190325	L1exclusions_20190325.pdf	1.000	exclusions	2019-03-25 00:00:00	exclusions	relief
5	L1_exclusions_20190418	L1exclusions_20190418.pdf	1.000	exclusions	2019-04-18 00:00:00	exclusions	relief
6	L3_modification_20190509	L3modification_20190509.pdf	3.000	modification	2019-05-09 00:00:00	modification	mixed
7	L1_exclusions_20190514	L1exclusions_20190514.pdf	1.000	exclusions	2019-05-14 00:00:00	exclusions	relief
8	L1_exclusions_20190604	L1exclusions_20190604.pdf	1.000	exclusions	2019-06-04 00:00:00	exclusions	relief
9	L1_exclusions_20190709	L1exclusions_20190709.pdf	1.000	exclusions	2019-07-09 00:00:00	exclusions	relief

Table 2: Summary of events with action type and direction

Summary of Events with LLM Columns

	event_id	file_name	list_id	doc_type	event_date	action_type	direction_guess	semiconductor_relevance	severity_label	direction	severity_ollama	surprise_ollama	direction_ollama	rationale_ollama
0	L1_noticeofaction_20180620	L1noticeofaction_20180620.pdf	1.000	noticeofaction	2018-06-20 00:00:00	imposition	tightening	True	3.000	tightening	2.000	0.400	relief	The proposed action is a partial revocation of trackage rights to expire after a limited time period, promoting rail transportation policy by eliminating the need for a second pleading. This decision is consistent with the limited scope of the transaction and will not adversely affect the current competitive situation of any shipper.
1	L2_noticeofaction_20180816	L2noticeofaction_20180816.pdf	2.000	noticeofaction	2018-08-16 00:00:00	imposition	tightening	True	3.000	tightening	2.000	0.600	tightening	The tariff increase on Chinese products will have a moderate impact on semiconductor-related firms due to the significant trade value of $16 billion and the broad scope of the tariffs, which affect various industries including technology and innovation.
2	L3_noticeofaction_20180921	L3noticeofaction_20180921.pdf	3.000	noticeofaction	2018-09-21 00:00:00	imposition	tightening	True	3.000	tightening	3.000	0.800	tightening	High impact due to significant tariff increase on products from China, affecting US exports and economy; the surprise is moderate as this action was expected by market participants.
3	L1_exclusions_20181228	L1exclusions_20181228.pdf	1.000	exclusions	2018-12-28 00:00:00	exclusions	relief	True	2.000	relief	2.000	0.500	relief	The U.S. Trade Representative established product exclusions for certain Chinese products, including semiconductor-related items, which will relieve some of the tariffs imposed on China.
4	L1_exclusions_20190325	L1exclusions_20190325.pdf	1.000	exclusions	2019-03-25 00:00:00	exclusions	relief	True	2.000	relief	2.000	0.700	relief	The USTR has granted product exclusions for certain Chinese products, including those used in semiconductors, reducing the scope of additional duties on China.

Table 3: Summary of events with LLM outputs and rationale text

Full Summary of Events by Firm with All Measures (Top 5)

	event_id	ticker	event_trading_date	severity_label	direction	severity_ollama	surprise_ollama	direction_ollama	CAR_window	CAR	alpha_hat	beta_hat	n_est	n_ev
0	L1_noticeofaction_20180620	005930.KS	2018-06-20 00:00:00	3.000	tightening	2.000	0.400	relief	[-5,5]	-0.027	0.000	0.274	100.000	11.000
1	L1_noticeofaction_20180620	3576.TW	2018-06-20 00:00:00	3.000	tightening	2.000	0.400	relief	[-5,5]	-0.171	-0.001	-0.018	100.000	11.000
2	L1_noticeofaction_20180620	6505.TW	2018-06-20 00:00:00	3.000	tightening	2.000	0.400	relief	[-5,5]	-0.032	0.001	-0.119	100.000	11.000
3	L1_noticeofaction_20180620	AAPL	2018-06-20 00:00:00	3.000	tightening	2.000	0.400	relief	[-5,5]	-0.018	0.001	1.065	100.000	11.000
4	L1_noticeofaction_20180620	AMD	2018-06-20 00:00:00	3.000	tightening	2.000	0.400	relief	[-5,5]	-0.030	0.002	1.496	100.000	11.000

Table 4: Full event summary by firm with all measures

Summary Statistics of LLM Severity/Surprise Measures

	severity_ollama	surprise_ollama
count	36.000	36.000
mean	2.250	0.437
std	0.937	0.262
min	0.000	0.000
25%	2.000	0.312
50%	2.000	0.425
75%	3.000	0.600
max	3.000	1.000

Summary Statistics of LLM Direction Measure

	direction_ollama	count
0	relief	22.000
1	tightening	8.000
2	None	7.000
3	mixed	4.000
4	high	1.000
5	unknown	1.000

Table 5: Summary statistics of LLM measures

11.2 Figures

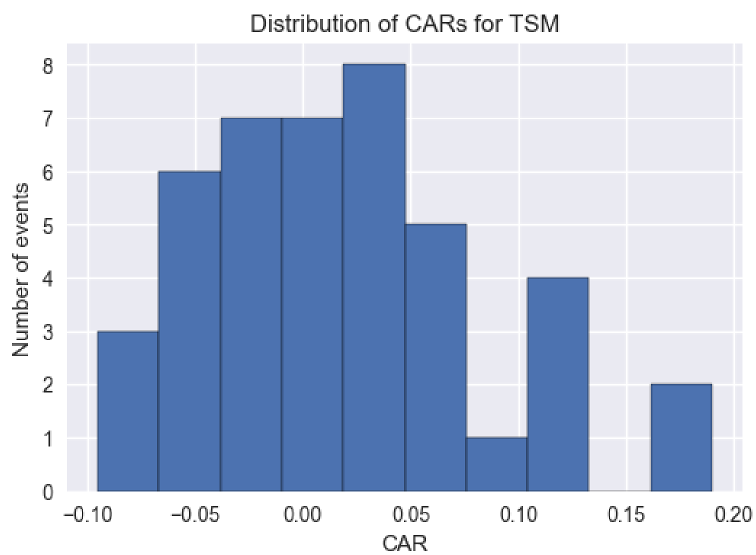

Figure 1: Distribution of CARs for TSMC

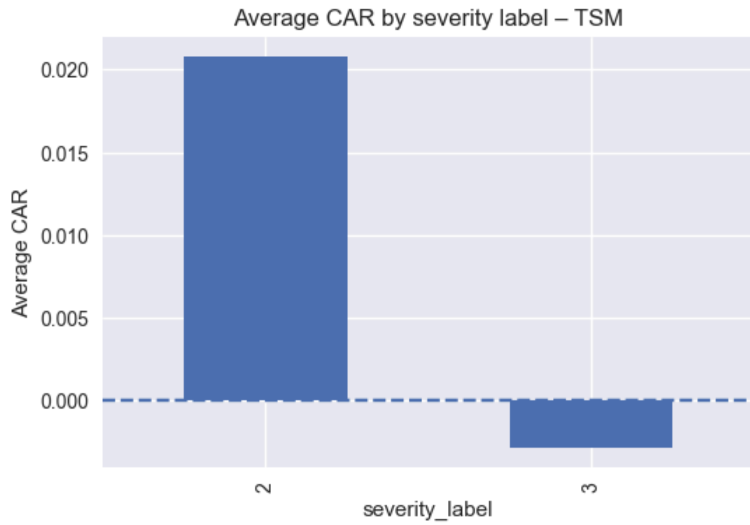

Figure 2: Average CARS by Severity for TSMC

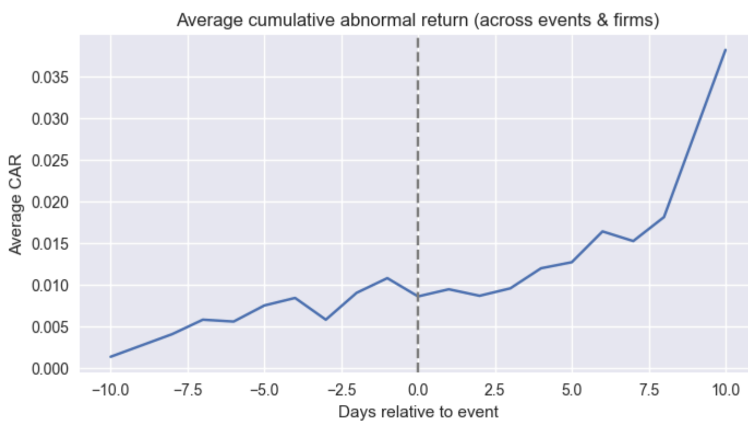

Figure 3: Average CAR for all events and firms

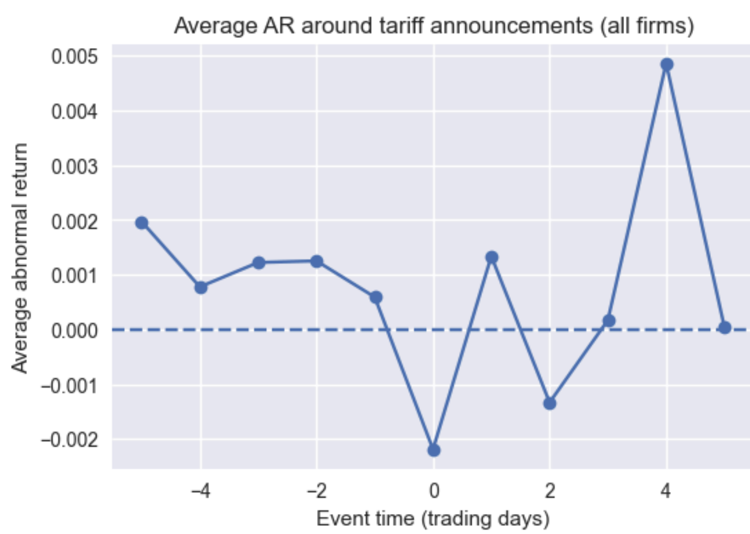

Figure 4: Average AR around announcements for all firms

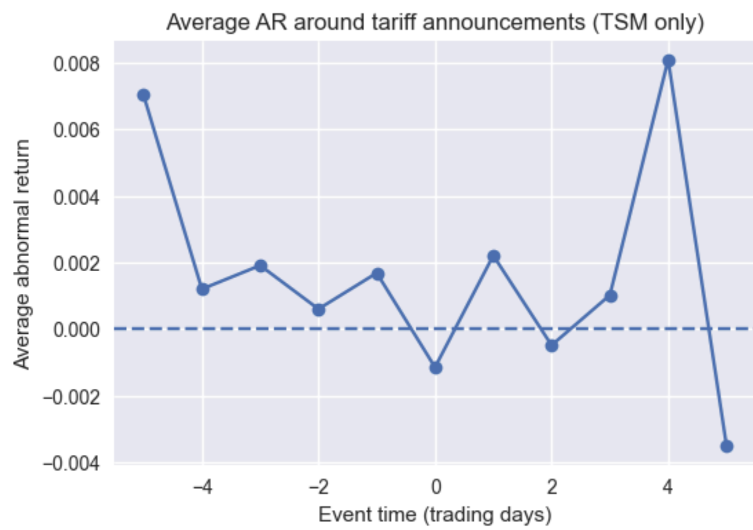

Figure 5: Average AR around announcements for TSMC only

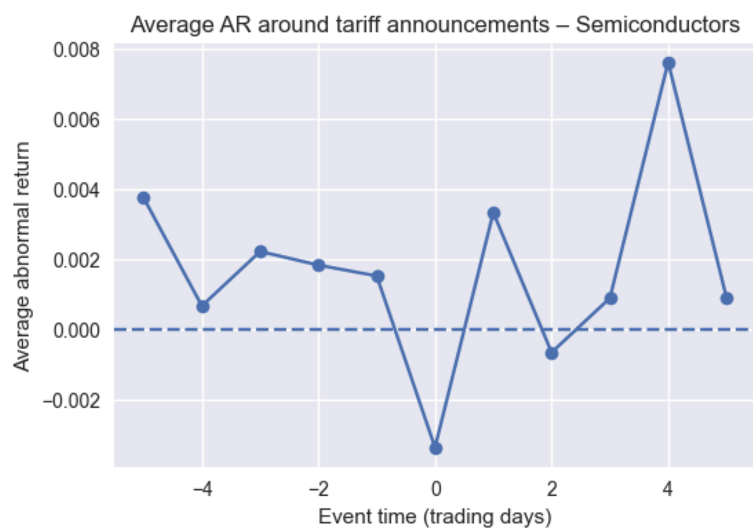

Figure 6: Average AR around announcements for semiconductor sector

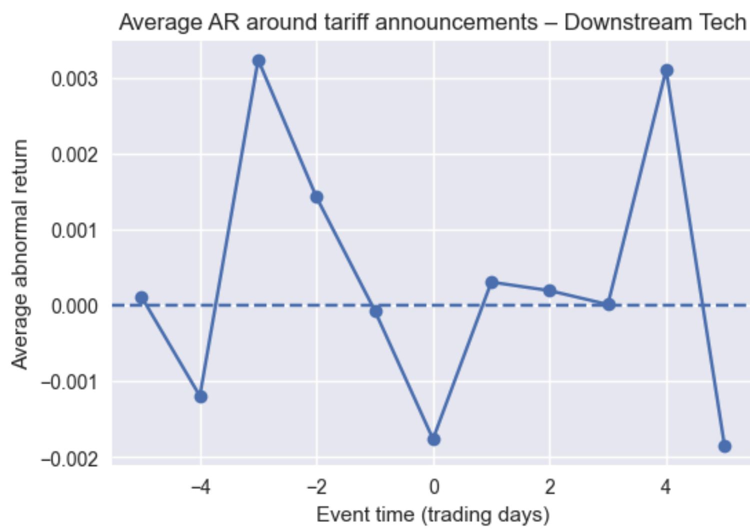

Figure 7: Average AR around announcements for downstream tech sector

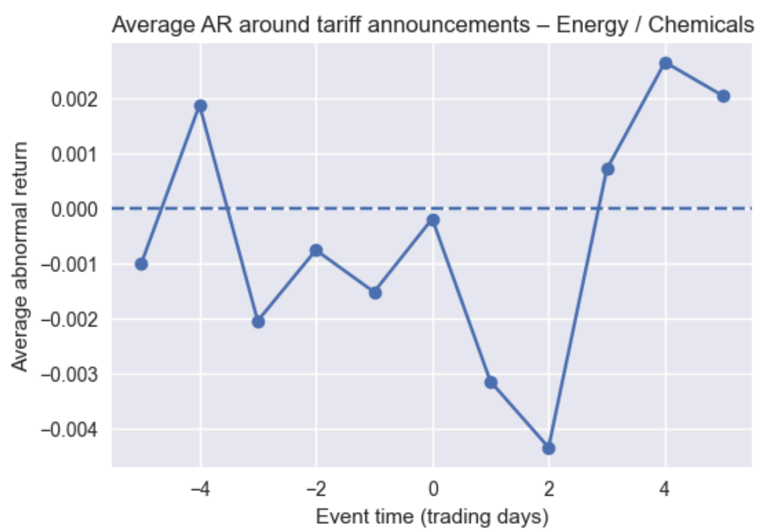

Figure 8: Average AR around announcements for energy/chemicals sector

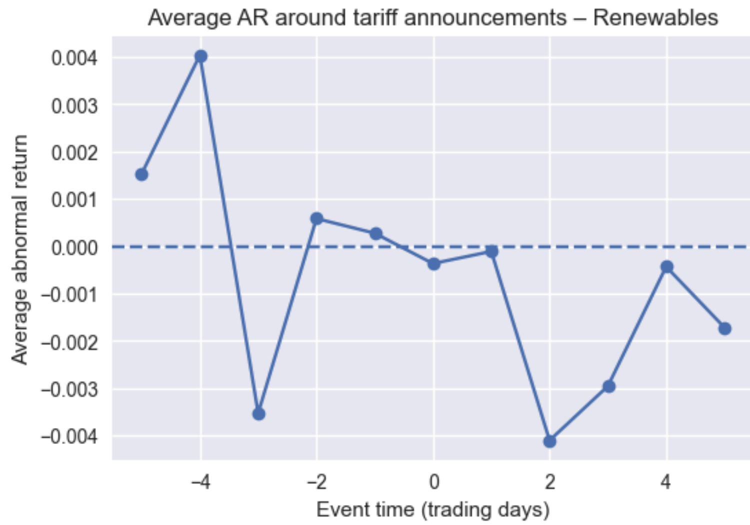

Figure 9: Average AR around announcements for renewables sector

11.3 Regression Summaries

OLS Regression Results

Dep. Variable:	CAR	**R-squared:**	0.006
Model:	OLS	**Adj. R-squared:**	-0.000
Method:	Least Squares	**F-statistic:**	31.06
Date:	Wed, 10 Dec 2025	**Prob (F-statistic):**	1.02e-08
Time:	12:49:23	**Log-Likelihood:**	354.68
No. Observations:	344	**AIC:**	-703.4
Df Residuals:	341	**BIC:**	-691.8
Df Model:	2		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.0025	0.002	-1.212	0.225	-0.007	0.002
severity_manual_num	-0.0010	0.003	-0.313	0.754	-0.007	0.005
dir_m_mixed	-0.0218	0.005	-4.666	0.000	-0.031	-0.013
dir_m_relief	0.0153	0.006	2.738	0.006	0.004	0.026
dir_m_tightening	0.0040	0.007	0.558	0.577	-0.010	0.018

Omnibus:	55.944	**Durbin-Watson:**	1.463
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	522.050
Skew:	-0.250	**Prob(JB):**	4.35e-114
Kurtosis:	9.014	**Cond. No.**	3.76e+15

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

Regression 1: CAR Manual Model

OLS Regression Results

Dep. Variable:	CAR	**R-squared:**	0.013
Model:	OLS	**Adj. R-squared:**	-0.008
Method:	Least Squares	**F-statistic:**	5.898
Date:	Wed, 10 Dec 2025	**Prob (F-statistic):**	0.000569
Time:	12:49:35	**Log-Likelihood:**	293.26
No. Observations:	288	**AIC:**	-572.5
Df Residuals:	281	**BIC:**	-546.9
Df Model:	6		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	0.0153	0.008	1.951	0.051	-6.75e-05	0.031
severity_ollama_num	-0.0054	0.006	-0.923	0.356	-0.017	0.006
surprise_ollama_num	0.0102	0.021	0.487	0.626	-0.031	0.051
dir_llm_high	0.0302	0.007	4.392	0.000	0.017	0.044
dir_llm_mixed	-0.0191	0.012	-1.622	0.105	-0.042	0.004
dir_llm_relief	0.0061	0.005	1.160	0.246	-0.004	0.016
dir_llm_tightening	-0.0041	0.008	-0.489	0.625	-0.020	0.012
dir_llm_unknown	0.0021	0.008	0.271	0.787	-0.013	0.017

Omnibus:	57.806	**Durbin-Watson:**	1.379
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	522.392
Skew:	-0.462	**Prob(JB):**	3.66e-114
Kurtosis:	9.533	**Cond. No.**	9.37e+15

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

Regression 2: CAR LLM Model

OLS Regression Results

Dep. Variable:	CAR	**R-squared:**	0.017
Model:	OLS	**Adj. R-squared:**	-0.011
Method:	Least Squares	**F-statistic:**	1.132
Date:	Wed, 10 Dec 2025	**Prob (F-statistic):**	0.366
Time:	12:49:44	**Log-Likelihood:**	293.85
No. Observations:	288	**AIC:**	-569.7
Df Residuals:	279	**BIC:**	-536.7
Df Model:	8		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.0001	0.004	-0.028	0.978	-0.007	0.007
severity_manual	0.0025	0.004	0.716	0.474	-0.004	0.010
severity_ollama	-0.0059	0.006	-0.932	0.352	-0.018	0.007
surprise_ollama	0.0128	0.021	0.602	0.547	-0.029	0.054
m_dir_m_mixed	-0.0182	0.008	-2.390	0.017	-0.033	-0.003
m_dir_m_relief	0.0153	0.006	2.608	0.009	0.004	0.027
m_dir_m_tightening	0.0027	0.008	0.327	0.743	-0.014	0.019
llm_dir_llm_high	0.0255	0.006	4.030	0.000	0.013	0.038
llm_dir_llm_mixed	-0.0218	0.013	-1.720	0.085	-0.047	0.003
llm_dir_llm_relief	0.0016	0.005	0.299	0.765	-0.009	0.012
llm_dir_llm_tightening	-0.0025	0.006	-0.399	0.690	-0.015	0.010
llm_dir_llm_unknown	-0.0029	0.010	-0.301	0.763	-0.022	0.016

Omnibus:	59.161	**Durbin-Watson:**	1.383
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	536.837
Skew:	-0.485	**Prob(JB):**	2.68e-117
Kurtosis:	9.618	**Cond. No.**	2.17e+16

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

Regression 3: CAR Combined Model

OLS Regression Results

Dep. Variable:	CAR	**R-squared:**	0.036
Model:	OLS	**Adj. R-squared:**	-0.012
Method:	Least Squares	**F-statistic:**	-2.660e+14
Date:	Wed, 10 Dec 2025	**Prob (F-statistic):**	1.00
Time:	13:01:21	**Log-Likelihood:**	56.732
No. Observations:	43	**AIC:**	-107.5
Df Residuals:	40	**BIC:**	-102.2
Df Model:	2		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.0458	0.004	-12.937	0.000	-0.053	-0.039
severity_num	-0.0010	0.004	-0.268	0.788	-0.008	0.006
dir_relief	0.0694	0.012	5.571	0.000	0.045	0.094
dir_tightening	0.0449	0.007	6.335	0.000	0.031	0.059

Omnibus:	2.746	**Durbin-Watson:**	1.146
Prob(Omnibus):	0.253	**Jarque-Bera (JB):**	1.903
Skew:	0.503	**Prob(JB):**	0.386
Kurtosis:	3.228	**Cond. No.**	7.03e+15

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

Regression 4: CAR Severity Index TSMC Only

OLS Regression Results

Dep. Variable:	CAR	**R-squared:**	0.006
Model:	OLS	**Adj. R-squared:**	-0.000
Method:	Least Squares	**F-statistic:**	-1.257e+14
Date:	Wed, 10 Dec 2025	**Prob (F-statistic):**	1.00
Time:	13:01:21	**Log-Likelihood:**	354.68
No. Observations:	344	**AIC:**	-703.4
Df Residuals:	341	**BIC:**	-691.8
Df Model:	2		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.0259	0.005	-5.217	0.000	-0.036	-0.016
severity_num	-0.0005	0.005	-0.103	0.918	-0.010	0.009
dir_relief	0.0371	0.004	8.487	0.000	0.029	0.046
dir_tightening	0.0254	0.010	2.557	0.011	0.006	0.045

Omnibus:	55.944	**Durbin-Watson:**	1.463
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	522.050
Skew:	-0.250	**Prob(JB):**	4.35e-114
Kurtosis:	9.014	**Cond. No.**	1.70e+15

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

Regression 5: CAR Severity Index All Firms

OLS Regression Results

Dep. Variable:	CAR	**R-squared:**	0.006
Model:	OLS	**Adj. R-squared:**	-0.000
Method:	Least Squares	**F-statistic:**	7.865e+13
Date:	Wed, 10 Dec 2025	**Prob (F-statistic):**	4.29e-243
Time:	13:01:35	**Log-Likelihood:**	354.68
No. Observations:	344	**AIC:**	-703.4
Df Residuals:	341	**BIC:**	-691.8
Df Model:	2		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	-0.0259	0.005	-5.217	0.000	-0.036	-0.016
C(direction)[T.relief]	0.0371	0.004	8.487	0.000	0.029	0.046
C(direction)[T.tightening]	0.0254	0.010	2.557	0.011	0.006	0.045
severity_num	-0.0005	0.005	-0.103	0.918	-0.010	0.009

Omnibus:	55.944	**Durbin-Watson:**	1.463
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	522.050
Skew:	-0.250	**Prob(JB):**	4.35e-114
Kurtosis:	9.014	**Cond. No.**	1.76e+15

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

Regression 6: CAR Severity & Direction

OLS Regression Results

Dep. Variable:	CAR	**R-squared:**	0.021
Model:	OLS	**Adj. R-squared:**	0.003
Method:	Least Squares	**F-statistic:**	19.65
Date:	Wed, 10 Dec 2025	**Prob (F-statistic):**	2.78e-10
Time:	13:01:35	**Log-Likelihood:**	357.33
No. Observations:	344	**AIC:**	-700.7
Df Residuals:	337	**BIC:**	-673.8
Df Model:	6		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	-0.0293	0.007	-3.983	0.000	-0.044	-0.015
C(direction)[T.relief]	0.0371	0.004	8.437	0.000	0.028	0.046
C(direction)[T.tightening]	0.0271	0.011	2.532	0.011	0.006	0.048
C(sector)[T.Energy/Chemicals]	-0.0093	0.016	-0.573	0.567	-0.041	0.023
C(sector)[T.Other]	0.0151	0.009	1.661	0.097	-0.003	0.033
C(sector)[T.Renewables]	-0.0103	0.026	-0.392	0.695	-0.062	0.041
C(sector)[T.Semiconductors]	0.0153	0.009	1.741	0.082	-0.002	0.033
severity_num	-0.0022	0.005	-0.450	0.653	-0.012	0.008

Omnibus:	50.728	**Durbin-Watson:**	1.465
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	429.655
Skew:	-0.182	**Prob(JB):**	5.03e-94
Kurtosis:	8.463	**Cond. No.**	1.84e+15

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

Regression 7: CAR Severity, Direction, & Sector Fixed Effects