Classifying US Firms into Trade Peace and Trade War Stocks: an NLP Analysis of Earnings Call Transcripts Approach

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Summary

Abstract / Motivation

- **Objective:** Assess firms' sensitivity to global trade shocks by classifying them as **trade peace** or **trade war** stocks.
- **Approach:** Apply NLP techniques to 54,851 earnings call transcripts (Russell 1000, 2007–2025)
- **Evaluation:** Event study on cumulative abnormal returns (CARs) around major trade policy events
- **Key Insight:**
  - Models have limited ability to clearly separate the two groups
  - TF-IDF + Logistic Regression yields the highest CAR difference: **1.29%**

Research Methodology Overview

- **Data Sources**
  - Earnings call transcripts (2007–2025) via Ninjas API
  - Russell 1000 constituents and returns (2015–2025)
  - Loughran-McDonald sentiment dictionary
- **NLP Models Tested**
  - Bag-of-Words (BoW)
  - Sentiment-adjusted BoW (BoWws)
  - TF-IDF + Logistic Regression
  - FinBERT (Transformer-based model)
- **Validation Strategy** 7-day event windows around trade policy shocks to compute cross-sectional CAR differences
- **GitHub Repository**

U.S. Tariff Events (2014-2025)

Table: Key U.S. Tariff Events

Date	Event Description
12 Oct 2014	U.S. imposes tariffs on Mexican sugar in trade dispute
24 Apr 2017	U.S. imposes $\sim$20% countervailing duties on Canadian softwood lumber
08 Aug 2017	U.S. launches Section 301 investigation into Chinese IP theft
01 Jan 2018	U.S. imposes 30% tariff on solar panels, 20-50% on washing machines
01 Mar 2018	U.S. announces 25% tariffs on steel, 10% on aluminum (Section 232)
22 Mar 2018	US orders identification of Chinese products for tariffs
02 Apr 2018	China retaliates with 15-25% tariffs on $3B of U.S. goods
17 Sep 2018	Third wave: 10% tariffs on $200B of Chinese goods (Phase 3)
10 May 2019	U.S. raises Phase 3 tariffs from 10% to 25%
01 Feb 2025	U.S. imposes 25% tariffs on Canadian and Mexican imports
04 Feb 2025	"Liberation Day Tariffs": 25% on aircraft, tools, electronics
04 Mar 2025	China retaliates with 15% tariffs on U.S. agriculture
12 Mar 2025	U.S. reimposes steel/aluminum tariffs (25%)

Trade Policy Attention and Trade Policy Uncertainty

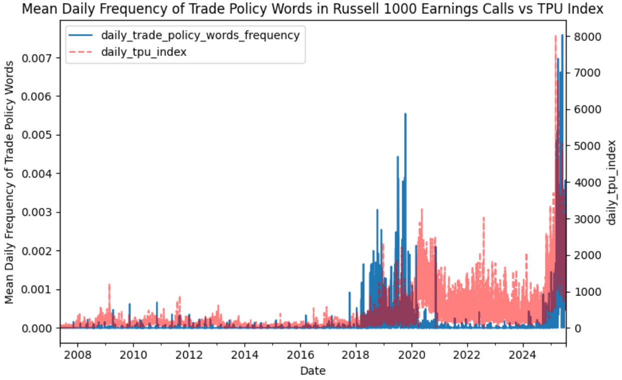

Figure: Mean Daily Frequency Trade Policy Words in Russell 1000 Earnings Call Transcripts vs TPU Index

Model 1: Bag-of-Words (BoW) Approach

Trade Score Formula:

$$Trade\ Score\ BoW = \frac{\sum_{w}^{W_T} \left(1_{w \in \text{keywords}}\right)}{W_T} \tag{1}$$

Classification Logic:

- **Trade Peace**: Firms mentioning 1 trade keyword in earnings calls
- **Trade War**: Firms mentioning 0 trade keywords
- Aggregated by quarter preceding event dates

Trade Dictionary (based on Baker, Bloom Davis 2016):

Trade Dictionary	
tariff	World Trade Organization
import duty	trade treaty
import barrier	trade agreement
import ban	trade policy
import tax	trade act
import subsidies	trade relationship
export ban	free trade
export tax	Doha round
export subsidies	Uruguay round
government subsidies	dumping
GATT	border tax
WTO	

Model 2: BoW with Sentiment (BoWws)

Trade Sentiment Formula:

$$Trade\ Sentiment = \frac{\sum_{w}^{W_T} \left(1_{w \in \text{keywords}} \cdot \sum_{c=w-10}^{w+10} S(c) \right)}{W_T} \tag{2}$$

Where $S(c)$ takes values:

- $+1$ for positive words (Loughran-McDonald dictionary)
- -1 for negative words
- 0 otherwise

Classification:

- **Trade Peace**: Positive trade sentiment
- **Trade War**: Negative trade sentiment

Model 3: TF-IDF + Logistic Regression

5-Step Process:

1. Convert transcripts to sentences
2. Zero-shot classification (facebook/bart-large-mnli) for preliminary sentiment labels
3. Threshold filtering for high-confidence sentences (optimized on 50 manually labeled sentences)
4. TF-IDF vectorization + logistic regression training
5. Majority voting aggregation to transcript level

Performance:

- Validation accuracy: 80%
- Training period: 2007-2019
- Test period: 2024-2025

Model 4: FinBERT (Transformer-based)

Trade Exposure Formula:

$$Trade\ Exposure = \overline{C_{neg}} - \overline{C_{pos}} \tag{3}$$

Where $\overline{C_{neg}}$ and $\overline{C_{pos}}$ are average negative and positive confidence scores of trade-related sentences.

4-Step Process:

1. Identify sentences containing trade-related keywords
2. Apply FinBERT sentiment classification (positive/negative/neutral + confidence)
3. Compute transcript-level trade exposure score
4. Classify based on exposure sign

Classification Logic:

- **Trade Peace**: Negative exposure score (more positive trade sentiment)
- **Trade War**: Positive exposure score (more negative trade sentiment)

Event Study Design

Objective: Test whether our classifications capture differential stock price reactions to trade policy shocks
Event Windows: 7 days (event day + 6 subsequent days)
Normal Returns Model (CAPM):

$$R_t^i = \alpha^i + \beta^i \times MKT_t + \varepsilon_t^i \tag{4}$$

Abnormal Returns:

$$AR_t^i = RR_t^i - NR_t^i = RR_t^i - (RF_t + \hat{\beta}^i \times MKT_t) \tag{5}$$

Cumulative Abnormal Returns:

$$CAR^i = \sum_{t \in \text{event window}} AR_t^i \tag{6}$$

Model Comparison: Cross-Sectional Mean CARs

Table: Summary table of cross-sectional mean CAR trade peace/war by model and event date

	BoW		BoWws		TF-IDF		FinBERT	
	peace	war	peace	war	peace	war	peace	war
2024-05-14	-0.02746	-0.02022	-0.05491	-0.01884	-0.00792	-0.03791	-0.03208	-0.02134
2025-02-01	-0.01287	-0.00631	-0.01538	-0.01358	-0.01488	-0.01270	-0.01493	-0.00759
2025-02-04	-0.01894	-0.01006	-0.01289	-0.02306	-0.02585	-0.01930	-0.02068	-0.01693
2025-03-04	-0.00698	-0.00648	-0.02450	-0.00111	0.03174	-0.00452	-0.00877	0.02579
2025-03-12	-0.01470	-0.00027	-0.02321	-0.01739	-0.00735	-0.01442	-0.01530	-0.00790
Mean	**-1.62**	**-0.87**	**-2.62**	**-1.48**	**-0.49**	**-1.78**	**-1.84**	**-0.56**

Key Findings:

- **BoW**: Mean difference = -0.75% (0% positive differences)
- **BoWws**: Mean difference = -1.13% (20% positive differences)
- **TF-IDF**: Mean difference = +1.29% (60% positive differences)
- **FinBERT**: Mean difference = -1.27% (0% positive differences)

Key Results Summary

Performance Ranking by Discrimination Ability:

1. **TF-IDF + Logistic Regression**: 1.29% absolute difference
    - Highest discrimination between trade peace/war stocks
    - 60% of events show expected directional differences
2. **BoWws (Sentiment-adjusted)**: 1.13% absolute difference
3. **BoW (Baseline)**: 0.75% absolute difference
4. **FinBERT (Baseline)**: 1.27% absolute difference

Unexpected Finding:

- Trade peace stocks often performed worse than trade war stocks
- Suggests that firms discussing trade may be more vulnerable rather than better prepared

Summary of Findings

Main Contributions:

- Developed and compared 4 NLP models for trade sensitivity classification
- TF-IDF + Logistic Regression emerged as best discriminator
- Event study validation shows measurable differences in stock reactions

Key Insights:

- Earnings calls contain valuable information about trade exposure
- Advanced NLP (TF-IDF + ML) outperforms simple keyword counting
- Firms mentioning trade may be signaling vulnerability rather than preparedness

Limitations and Future Work

Current Limitations:

- Statistical significance tests needed (Kolari & Pynnonen 2010 corrections)
- Limited sample size for TF-IDF model (2024-2025 test period)
- Mixed directional results across models

Future Research Directions:

- Implement Large Language Models (GPT-4, Claude) for classification
- Extend analysis to 10-K filings for broader coverage
- Test alternative ML algorithms (Random Forest, XGBoost)
- Develop sector-specific trade sensitivity measures

Policy and Investment Implications

For Investors:

- Earnings call analysis can inform trade-sensitive portfolio construction
- TF-IDF approach provides most reliable classification framework
- Consider contrarian approach: firms discussing trade may be more at risk

For Policymakers:

- Textual analysis can help predict heterogeneous firm responses to trade policy
- Earnings calls reveal private information about trade exposure
- May inform targeted policy interventions

For Corporate Management:

- Earnings call language may signal market perceptions of trade vulnerability
- Consider strategic communication around trade exposure

END

GitHub Repository

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