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# Measuring Income Group Heterogeneous Treatment Effect of Trade Openness on Unemployment Rate at Country-Year Level

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**Abstract**

Opening up to trade has alleviated millions of Chinese people from poverty, but also took many jobs away from Americans. What about the rest of the world? Does trade hit each country the same? I estimate the Heterogeneous Treatment Effects of trade openness on the unemployment rate among 180 countries from 1990 to 2020, using the latest trade volume measures and free trade agreements as trade openness measurements. Despite the potential bias of endogeneity problems, I found a strongly significant negative treatment effect for upper-middle income nations (e.g., China and Brazil), a positive effect with small significance for lower middleincome countries (e.g., India and Vietnam), a positive effect with no significance for low-income countries (e.g., African countries like Sudan, Guinea etc.), and a small but mixed effect for high income countries (mostly OECD countries). However, the total number of Free Trade agreements is not a perfect measurement and there are severe endogeneity problems that still need to be untangled in future studies.

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## Introduction

The effect of trade on employment is the center of the public trade policy debate (Davidson et al., 1999). Here are two paths from trade openness to labor markets that are demonstrated by protectionists who are against trade, and globalists who support free trade. Protectionists argue that lower production costs and little regulations in developing countries enable foreign firms to out-compete local production, thus resulting in less local output and jobs. Globalists argue that free trade expands export markets, increases the demand for domestic products, production, and jobs (Davidson et al., 1999). Theories and some empirical research argue that trade harms the import-competing industries. According to the classical Heckscher–Ohlin model, "firms of a country's abundant factors gain from trade, but firms of a country's scarce factors lose..." (Krugman and Obstfeld 2005, p64). Thus, the low-skilled workers may suffer on a sustained basis in high income group countries with abundant high skill labor and scarce low skill labor. Following this logic, Trefler (2004) used industry-level and plant-level data to estimate NAFTA's effect in the Canadian labor market and found that tariff reduction led to reduction in employment. McLaren et al. found a dramatically lowering wage growth caused by NAFTA for low-skilled workers in import competing industries, and even for service-sector workers in related localities using US census data from 1990 to 2000 (2011). Autor et al. (2016) investigated the trade effect in the local labor markets in concentrated import-competing industries and found that employment has decreased in the import competing industry. Carrère et al. has built a model based on the Ricardian model using sector-specific matching frictions to estimate the trade effect on labor market, and they found that trade brings more employment in sectors with comparative advantage and higher efficient labor markets, vice versa (2016). Following this logic, I expected to see that more trade benefits low- and middle-income countries' labor markets and worsens the high-income group countries labor markets. Some other empirical research argues that labor markets benefit from trade. Felbermayr et al. found that an increase in total trade openness reduces aggregate unemployment in 20 OECD countries from 1983 to 2003 (2011). Belenkiy et al. (2015) concluded that an expansion in international trade tends to reduce a country's long-term aggregate unemployment rate based on multiple empirical studies.

## Uniqueness and paper structure

The uniqueness of this study is to use Free Trade Agreements as a trade openness measurement to as best as possible avoid the endogenous problems between trade volumes and unemployment rate. In the remainder of the paper, I will first present the causal chain by introducing Free Trade Agreement (FTA) and argue the necessity to assume heterogeneous treatment effects. Then, the usual technical items in the Method session: data description, estimation strategy, a parallel trend test to justify the usage of unit-specific trends. Results sessions present regression results and problems with measurements. Robustness checks section presents three robustness checks. The first one is to test how solid the first step in the causal chain is. The second presents an alternative way to conduct the regression without HTEs interaction, while the third is a reduced form estimation using FTAs as instrumental variable . The discussion section summarizes the shortcomings and evaluates the validity of results. The conclusion offers takeaways.

## Free Trade Agreement and Causal chain

By definition, a Free Trade Agreement (FTA) is set to reduce trade barriers between two or more nations. It demonstrates the willingness for a nation to trade. Hence, it naturally qualifies to present the trade openness. The FTAs are relatively exogeneous, because the making of FTAs requires consensus among multiple nations. However, FTA is not a perfect, it can be correlated with domestic politics, as we do observe that politicians interfere with trade policy such as seen when the Trump administration withdrew from the Trans-Pacific Partnership. Thus, there is a possibility that FTAs can be correlated to endogenous elements. Further validation will take place in the discussion section.


Since FTA is designed to reduce the trade barriers, then we should expect that FTA may induce more trade, which means an increase in trade openness. This FTA induced change in trade volume will impact the labor market. The multidate and direction of impacts is different depending on the labor market structure. Thus, it will be necessary to assume heterogeneous treatment effects (HTEs).

## Why heterogeneity treatment effects (HTEs)?

The reasons for using heterogeneous treatment effects are the following. First, a country's labor structure tends to vary based on income. Rich countries tend to have a different labor structure compared to poor countries, i.e., more high-skilled labor for the rich countries, and more lowskilled labor for poor countries. Thus, trade openness will have heterogeneous treatment effects in poor countries compared to rich countries. Second, my empirical estimation below also confirms this logic.

**Table 1 Suggestive evidence that the relationship might vary by income level**

| | | Unemployment rate | | | |
|---|---|---|---|---|---|
| | All observations | Low income | High income | Upper middle income | Lower middle income |
| Trade | 0.00102 | 0.00584*** | 0.00134 | -0.0164*** | 0.0128*** |
| | (0.00152) | (0.00208) | (0.00232) | (0.00404) | (0.00329) |
| Constant | -599.3*** | 84.40 | 163.3 | -169.3 | -664.7*** |
| | (160.9) | (55.71) | (304.0) | (119.9) | (125.9) |
| Observations | 4,791 | 654 | 1,582 | 1,307 | 1,248 |
| R-squared | 0.921 | 0.959 | 0.808 | 0.940 | 0.953 |

## Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

According to the table, when using different income groups samples, there are difference in significance, sign of coefficient, magnitude of the treatment effect, comparing to using the whole sample. Thus, we need an HTE approach for the main estimation strategy.

## Data

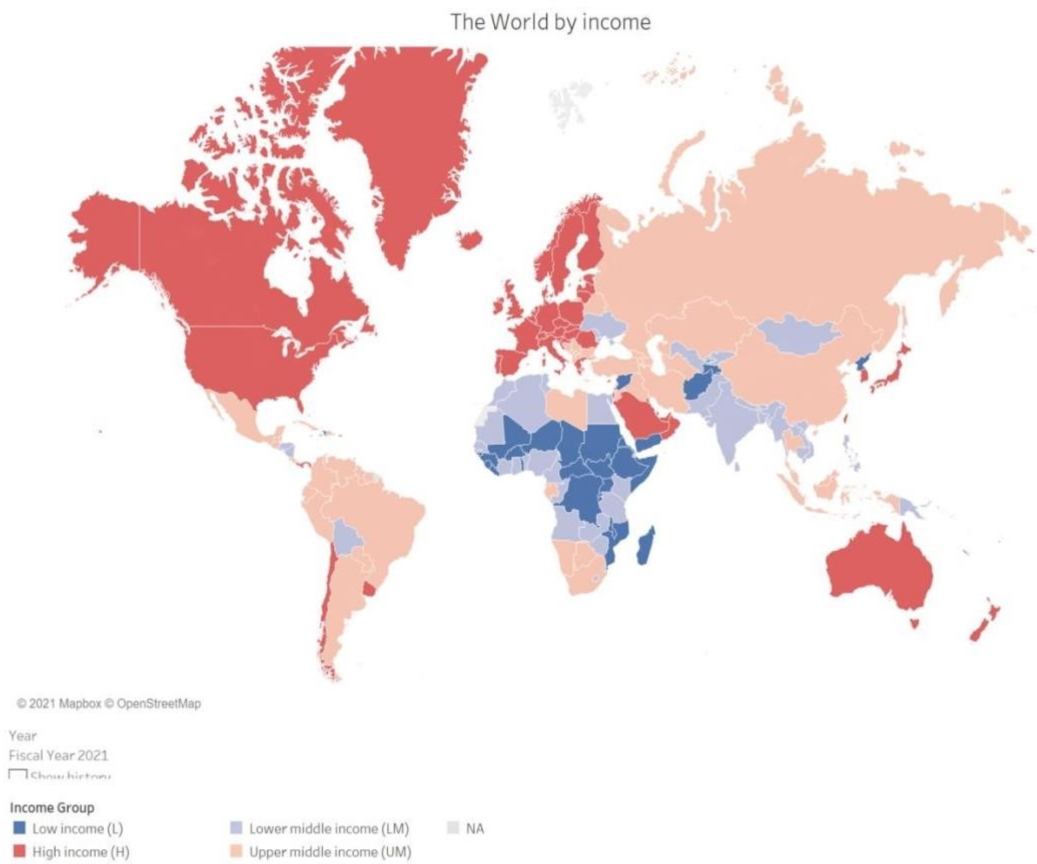
The paper relies on a merged panel data with country-year being the unit of analysis. After cleaning, the dataset contains 180 countries as cross-sectional units, and a time range from 1991 to 2019.

### The dependent variable is a measurement of unemployment.

I use the International Labor Organization's weighted average unemployment rate. The unemployment rate represents the share of the labor force that doesn't have a job but is ready to work and is looking for employment. The unemployment rate data is from the International Labor Organization and World development indicator database, ILOSTAT database.

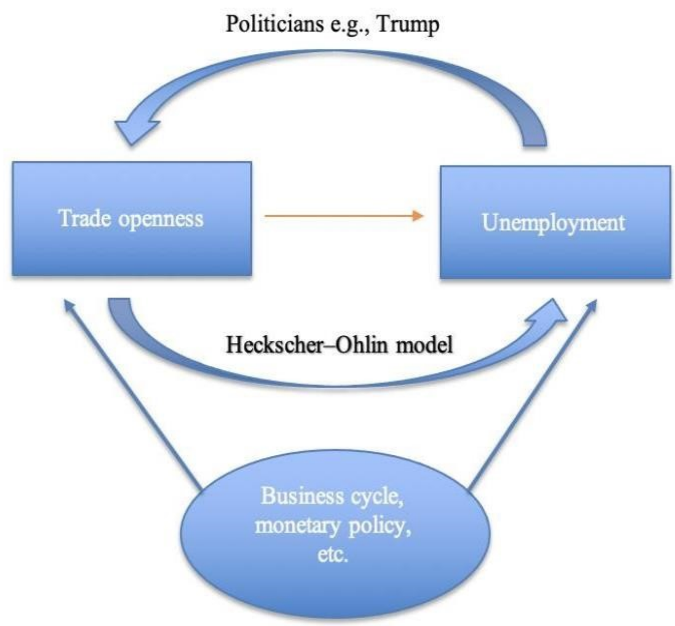
### The policy variable is a measurement of trade openness.

I use nominal exports, imports, trade (export plus import) share of nominal GDP as a policy variable in my final analysis. The openness to trade is usually measured by the sum of nominal imports and exports relative to nominal GDP for simplicity (Felbermayr et al., 2011). However, the real-world debate is usually centered around foreign imports' damage to domestic economies. Thus, I am also including exports and imports. Trade data is from the World Bank national accounts data, and the OECD National Accounts data files. For the total trade agreement per year at the country level, I use the Mario Larch's Regional Trade Agreements Database from Egger and Larch (2008). It has 516 agreements (active and inactive) in the dataset from 1950 to 2019, differentiated by seven categories, e.g., regional trade agreement, free trade agreement etc. The income group categorical data is from the World Bank. For analytical purposes, the World Bank uses gross national income (GNI) per capita data to classify economies into four income groups every year, please see the map below. The GNI data is applied with World Bank Atlas method to smooth the exchange rate fluctuation




## Endogeneity problems

It is not a surprise that previous studies of trade on labor effects are very divided. The measure of trade effects on the labor market is messy. Trade policy is dynamic, multidimensional. One country's trade policy change could be induced by its trading partners' behaviors. In the case of economic opening, it is hard to identify the impact of trade on labor markets due to the shock caused by a mixture of trade, trade barriers and investment flows (Autor et al. 2016). In general, in the short run, the labor market is affected by aggregate demand factor, e.g., monetary policy (Belenkiy et al. 2015). In the long run, both the labor market and trade openness are affected by the business cycle. Besides business cycle and monetary policy, as mentioned by Felbermayr et al. (2011), a reverse causality may appear due to a negative spurious correlation between unemployment and trade openness caused by political incentives to induce trade barriers to respond to unemployment shocks, e.g., Trump administration initiated the China-US trade war. Also, a special situation of simultaneously increasing imports and decreasing unemployment may occur when the timing of trade liberalization and labor market reform coincide, e.g., China's open-up reform in 1980.s.




Test for parallel trend

| | | |
|---|---|---|
| year | -0.0489*** | assumption -- strong correlation between time variable (year) and the first difference of unemployment rate before 2001. Hence, a unit-specific trend estimation will be the right strategy to capture the heterogeneity at country-year level. |
| | (0.0107) | |
| Constant | 97.81*** | |
| | (21.39) | |
| Observations | 1,416 | |
| R-squared | 0.015 | |

Table 2 Test for parallel trend assumption

**Estimation strategy**

My estimation specification strategy estimates the heterogeneous treatment effects with a year, country fixed effect and unit-specific trend.

*Equation 1*

$$Unemployment_{it} = \gamma_0 + \gamma_1\, TradeOpeness_{it} +$$

$$\gamma_2\, TradeOpeness_{it} IncomeGroup_i + \vec{\gamma}_3\, IncomeGroup + \lambda_t + \alpha_i + U_i + \varepsilon_{it}$$ [1]

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- [1] t -- year
- i – country
- $\lambda_t$ – time fixed effect
- $\alpha_i$ – country fixed effect
- $U_i$ – unit specific trend
- $Unemploymentit$– The unemployment is measured by a weighted average unemployment rate for year t in country i. It is a percentage of total unemployment as a share of the total labor force.
- $TradeOpeness_{it}$– The trade openness measured by total free trade agreements for country i in year t and the volume (the percentage of nominal export, or import, or the sum of both to nominal GDP ratio.)
- $TradeOpeness_{it}IncomeGroup_i$– An interaction of trade openness and income group. It serves to estimate the heterogeneity effect of trade openness conditioned different income group.

## Results

**Table 3: Using trade volume to measure openness, estimating HTEs by interaction**

| | | Unemployment rate | |
|---|---|---|---|
| Trade openness measurement | Imports | Exports | Trade |
| TO x High income | -0.000944 | 0.00804** | 0.00194 |
| | (0.00393) | (0.00383) | (0.00200) |
| TO x Low income | 0.00593 | 0.0250** | 0.00536 |
| (ref: High) | (0.00659) | (0.0116) | (0.00449) |
| TO x lower middle income | 0.0141* | 0.0131 | 0.00859* |
| (ref: High) | (0.00744) | (0.00901) | (0.00451) |
| TO X upper middle income | -0.0170** | -0.0347*** | -0.0164*** |
| (ref: High) | (0.00732) | (0.00743) | (0.00410) |
| Effect size | 0.0031135 | 0.008076 | 0.0060973 |
| Observations | 4,791 | 4,791 | 4,791 |
| R-squared | 0.921 | 0.922 | 0.921 |

**Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.**

For high-income groups, imports have a negative treatment effect on the unemployment rate at a very small scale, and to my surprise, exports have a positive treatment effect with a significance at 5%. Compared to high-income groups, low-income group countries have much larger positive estimates, which means trade openness is associated with more job loss, especially for Exports, since it has a 5% significance. But, interestingly, the loudest complainers of international trade are never the poor countries. For lower-middle-income countries, trade openness is positively associated with the unemployment rate. The ultimate winners are upper-middle-income countries, which experience a decrease in the unemployment rate while an increase in trade openness.

| Trade openness measurement | Unemployment rate |
|---|---|

| | |
|---|---|
| #FTAs x high income group | 0.0111**<br>(0.00519) |
| #FTAs x low group (ref: high) | 0.141<br>(0.129) |
| #FTAs x lower middle (ref: high) | 0.00847<br>(0.0234) |
| #FTAs x upper middle (ref: high) | -0.0335**<br>(0.0143) |
| Effective size | 0.0016048 |
| Observations | 4,791 |
| R-squared | 0.921 |

This result is consistent with the one using trade volume. The difference here is more statistical significance for the highincome group, and less for low and lower middle income. Also, the estimate for the high-income group has a larger effect. Although we can't conclude that the trade agreements do more har than just export or import for high-income countries, it is worth thinking if trade agreement is more unsatisfying for the high-income group compared to others, e.g., Brexit.

**Robustness checks**
**Table 5 First step in the causal chain: from FTA to trade volume**

| | Imports of goods and services (% of GDP) | Exports of goods and services (% of GDP) | Trade (% of GDP) |
|---|---|---|---|
| #FTAs x higher income | -0.0103 | 0.0184 | 0.00810 |
| | (0.0301) | (0.0260) | (0.0515) |
| #FTAs x for low income | 0.263 | -1.251* | -0.988 |
| (ref: High) | (0.748) | (0.647) | (1.280) |
| #FTAs x lower middle | 0.159 | 0.0805 | 0.239 |
| (ref: High) | (0.135) | (0.117) | (0.232) |
| #FTAs x upper middle | 0.0794 | 0.00389 | 0.0833 |
| (ref: High) | (0.0826) | (0.0715) | (0.142) |
| Observations | 4,791 | 4,791 | 4,791 |
| R-squared | 0.882 | 0.923 | 0.911 |

**Standard errors in parentheses ***p<0.01, ** p<0.05, * p<0.1.**

According to the table, the free trade agreement didn't induce significant trade volume. I note that there is only one 10% significance for a quite large-scale decrease of exports volume with one more FTA among the low-income group countries. Regardless of significance or magnitude, more free trade agreement generally increases the trade volumes except for higher-income group countries' imports, low-income exports, and trade.

## Estimation without HTEs

To verify the robustness of my result, I conducted regular unit-specific trend regression within each income group.

*Equation 2*

$$Unemployment_{it} = \gamma_0 + \gamma_1\, TradeOpeness_{it} + \gamma_2\, TradeOpeness_{it} + \lambda_t + \alpha_i + U_i + \varepsilon_{it}$$

**Table 6: Estimation by income groups**

| | | | | | | Unemployment rate | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | High | | Upper middle | | | | Lower middle | | | Low | |
| Imports | -0.00210 | | | -0.0172** | | | 0.0164*** | | | 0.00328 | | |
| | (0.00453) | | | (0.00691) | | | (0.00505) | | | (0.00275) | | |
| Exports | | 0.00697 | | | -0.0337*** | | | 0.0242*** | | | 0.0294*** | |
| | | (0.00445) | | | (0.00722) | | | (0.00676) | | | (0.00559) | |
| Trade | | | 0.00134 | | | -0.0164*** | | | 0.0128*** | | | 0.00584*** |
| | | | (0.00232) | | | (0.00404) | | | (0.00329) | | | (0.00208) |
| Effective size | .0001496 | .0017068 | .0002334 | .005226 | .0181316 | .0138323 | .0093342 | .0112648 | .0132219 | .002473 | .0459341 | 0.0135446 |
| Observations | 1,582 | 1,582 | 1,582 | 1,307 | 1,307 | 1,307 | 1,248 | 1,248 | 1,248 | 654 | 654 | 654 |
| Countries | 58 | 58 | 58 | 49 | 49 | 49 | 47 | 47 | 47 | 26 | 26 | 26 |

**Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.**

The results of upper-middle-income group and lower-income groups are consistent with previous estimations. The difference here is the strong statistical significance in the positive relationship between trade volume and unemployment rate for lower-middle-income and low-income groups. Even though this robustness check has fewer samples per group, it generates stronger statistical significance.

## Reduced form – using FTAs as an instrumental variable

This regression measures the effect of trade volume induced by free trade agreements impacting the unemployment rate. Even though the number of FTAs is not suitable as an instrumental variable as the first robustness check suggested, this estimation has its value in uncover a relatively endogeneity-free unidirectional effect

**Table 7 Reduced form (1) strategy, with trade volume instrumented by #FTAs**

| | | Unemployment rate | |
|---|---|---|---|
| Trade openness measurements: | Import | Export | Trade |
| TO x high income | 0.00308 | 0.00928 | 0.00372 |
| | (0.0644) | (0.0444) | (0.0167) |
| TO x Low income (ref: High) | 0.751 | -0.127 | -0.122 |
| | (1.117) | (0.180) | (0.152) |
| TO x Lower middle income (ref: High) | -0.0341 | -0.0513 | -0.0188 |
| | (0.212) | (0.176) | (0.0611) |
| TO x Upper middle income (ref: High) | -0.208 | -0.720 | -0.198 |
| | (0.467) | (1.389) | (0.200) |
| Observations | 4,791 | 4,791 | 4,791 |
| R-squared | 0.547 | 0.716 | 0.860 |

## Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The results of upper middle income and high-income group countries are consistent with previous estimations. However, all statistical significance disappeared, and the sign flipped for some estimations, e.g., the Export and Trade estimates for low-income, and all for lower middle income. The flipping sign could be caused by the correlation of trade volume and fluctuations in business cycles. It is worth noting the magnitude of coefficients is larger than previous ones. For example, upper-middle export and low import estimates are the only ones that exceed the Minimum Effect Size (see below table).

## Discussion

The study is likely to be underpowered based on the effect size table below. None of the effects results exceeded the Minimum Detectable Effects (MDEs) except some estimates in the Reduced Form (table 7).

Table 8 Minimum Detectable Effect table by income groups and all

| | High | Low | Upper middle | Lower middle | All |
|---|---|---|---|---|---|
| Unemployment standard deviation | 4.33 | 4.10 | 7.42 | 5.94 | 6.02 |
| Delta calculated by OD[1] | 0.14 | 0.21 | 0.15 | 0.16 | 0.082 |
| Number of observations | 1582 | 654 | 1307 | 1248 | 4791 |
| MDE | 0.61 | 0.89 | 1.15 | 0.95 | 0.49 |

All numbers are rounded to 2 decimal places. There are problems associated with using the number of Free Trade agreements, as a measure of treatment. First, free trade agreements (FTAs) cannot induce significant trade flows. It could be because of the low number of cases in a monadic dataset, since free trade agreement tends to be analyzed dyadically. It also could be because that there is a lagged effect of FTA on trade volume, thus the total number of free trade agreements may not be able to capture the positive relationship between FTAs and trade volume. Further time series related FTA investigation will be helpful for further research. Also, an omitted variable bias may occur when FTA serves as a signal to domestic investors. Investors may invest more in the export-oriented industries, i.e., start a factory and hire more workers. Thus, FTAs may affect labor markets not through the change of trade volumes, but through signaling effects. However, due to its relative exogenous property, i.e., it requires collective consensus among countries and takes a long time to settle, there are less endogenous elements correlated with FTAs compared to trade volume. Thus, I am confident in using total numbers of FTAs as a measurement of treatment.

## Conclusion

Despite the multiple endogeneity problems (reverse causal relationship, business cycle), I am confident about several results below. The upper-middle income nations are the ultimate winners from trade openness. All regressions suggest that upper-middle-income countries' (e.g., China) labor markets benefit from the increased trade. Trade openness has a negative impact on labor markets in lower middle- and low-income countries. However, the import effect on high income countries' labor markets remains inconclusive. It is worth mentioning that the low-income group countries have a positively larger magnitude of treatment effects than high income group countries among all results. This is surprising given that low-income countries don't appear to be the strongest protectionists on the international stage. It is worth questioning that, while high income countries enjoy the cheap imports, and upper middle-income countries' development benefits from trade, are lower middle- or low-income group countries still benefiting from trade openness? The results presented in this paper suggest that they are not. However, the question remains open for further research that enables a cleaner treatment effect with less endogeneity.

## Future Research Directions

The advent of technology has facilitated the development and implementation of sophisticated machine learning models, e.g.,Convolutional Neural Networks (Zhan et al., 2022), Deep Learning Model, or one can use Bayes models (Zhan et al., 2020). These models have found practical applications in diverse fields, including e-commerce (Wu and Chi, 2024), transportation (X. Ma et al., 2024c). Notably, their autonomous pattern-learning capabilities offer potential solutions to challenges discussed in this paper, particularly in addressing issues related to the segregation of treatment effects and endogeneity, e.g., generating counterfactual examples using ReLAX (Chen et al., 2021). Furthermore, the adoption of such an approach necessitates an expanded dataset, which is advantageous, allowing the incorporation of additional factors such as the geographical proximity of countries and historical colonial situations. In the realm of predictive analytics and inference, state-of-the-art technologies like multimodal transformers have already been successfully deployed (Lyu et al., 2023). The impact of trade on domestic markets is intricate, encompassing tangible economic effects and perceived panics among the workforce, who also happen to be voters. It is noteworthy that trade policies and restrictions, exemplified by instances like the China-US trade war, are often significantly influenced by political considerations (Autor et al., 2023). Recognizing that policy makers

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base decisions on voter sentiments, it becomes imperative to incorporate public sentiment for a more nuanced decision-making process. A particularly valuable component in this regard is the integration of sentiment analysis, especially on social media platforms, to inform and shape more informed trade policy decisions (Zhu and Hu, 2021).The acceleration of real-time sentiment analysis in the cloud environment is notably enhanced through the incorporation of advanced technologies, exemplified by CloudEval-YAML (Xu et al., 2023d). Additionally, the integration of a Large Language Model (LLM), such as BERT-based models (Lyu et al., 2023), and ChatGPT (Jin et al., 2023),contributes substantively to the augmentation of Natural Language Learning analytical capacities within this computational framework).

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