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Inequality and Trade Openness in the U.S.

Is There a Significant Linkage?

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Inequality and Trade Openness in the U.S.: Is There a Significant Linkage?

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1 INTRODUCTION

Throughout the history of the economy, revolution has gone hand in hand with globalization. Since the existence of the Silk Road, trade had stopped being a local or regional affair and started to become global (Vanham, 2019). Then, economists have studied the benefits of specialization, trade openness, win-lose relationship of collaboration between specialized countries (Ricardo, 1817). In addition, the break in the global chain due to COVID-19, or Donald Trump's ideology of MAGA[1], once again raised the world's concern about "globalization".

Although theoretical models like Stolper-Samuelson predict that trade openness widens the income gap in developed economies like the U.S., empirical evidence remains mixed. While some researchers argue trade is the main driver of income inequality, others point to technological change. Existing literature presents two significant gaps that this study aims to address. First, most studies focus on cross-country analysis. There is a scarcity of studies specifically examining the U.S. economy over a long period to capture the trade-inequality relationship. Second, and most importantly, many previous studies overlook the role of fiscal policy. Taxation and spending, for instance, via which governments commonly redistribute income and mitigate inequality. Therefore, ignoring these variables can lead to omitted variable bias, making the estimated impact of trade inaccurate.

This paper aims to empirically examine the relationship between trade openness and income inequality in the U.S. economy. Specifically, we seek to determine whether a significant linkage exists and if the interaction between trade and inequality follows an error correction mechanism. Furthermore, this study distinguishes itself by incorporating fiscal policy variables (taxation and government spending) to control for omitted variable bias, providing a more robust test of the trade-inequality nexus.

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[1]Making America Great Again

2 LITERATURE REVIEW

2.1 Theoretical Framework

Aligned with "free-trade", the problem of protecting the equality in income distribution among the countries has also been brought by Stolper and Samuelson (1941)[2]. The theorem proves that, in an unskilled labor-abundant country, trade increases demand for unskilled workers, thus raising their wages and reducing the income gap with skilled workers. In contrast, capital-abundant country exports their intensive goods, benefiting capital owners and high-skilled laborers, so that increasing inequality. Therefore, this study analyzes the validity of the Stolper and Samuelson theorem about the income disparity in the U.S. economy.

2.2 Previous Studies

The relationship between trade openness and income inequality has been a subject of intense debate, yielding mixed empirical results. A comprehensive meta-analysis by Heimberger (2020) indicates that while economic globalization generally has a small-to-moderate inequality-increasing impact, this effect is driven more strongly by financial globalization (e.g., FDI) than by trade globalization. Cross-country studies, such as Meschi and Vivarelli (2009), suggest that trade with high-income countries specifically worsens income distribution in middle-income countries due to technological upgrading, but the evidence for high-income economies remains complex.

Despite the scarcity of specify research papers in the US, there is some strong evidence showing how trade shocks directly affect inequality. A study by Autor et al. (2013) examined the rise of Chinese imports between 1990 and 2007. They found that local areas in the U.S. that faced more competition from China lost a significant number of manufacturing jobs and saw lower wages. This mainly hurt low-skilled workers, which directly led to a rise in inequality in those regions. Apart from potential dynamic linkage, Barusman and Barusman (2017) uses OLS regression method to identify the influence of trade openness on income inequality in the U.S. via multiple independent variables. Regardless limit of the sample size (1970 - 2014), the estimation results when using Gini as dependent variables[3] display that both 2 sides of trade (export and import) are associated with positive effect on income inequality, and the export side has a greater impact.

However, many studies argue that the impact of trade on inequality in the U.S. is relatively small. Lawrence (2008) counters the view that trade drives inequality, positing that international trade accounts for only a small fraction of the rise in U.S. income inequality. He suggests that the widening gap is primarily driven by skill-biased technological change rather than import competition. This perspective is supported by Krugman (2008), who revisited the trade-wage debate and concluded that the effect of trade on aggregate inequality remains modest. Krugman argued that although imports from developing countries have increased, the volume of trade is still insufficient to be the primary culprit for the massive surge in the U.S. wage gap.

[2] Regarding the Heckscher-Ohlin model, the model assumes free trade between 2 countries with 2 goods and 2 factors of production. And Samuelson's study was based on that model foundation.

[3] The paper uses 2 types of dependent variables - Gini and top 10% Income share

Besides, the role of fiscal policy, specifically taxation and government spending, remains central to modern distributional analysis. Garcia Rojas et al. (2025) provides strong empirical evidence from the 1990 to 2019 period demonstrating that economic growth alone is insufficient to reduce inequality unless accompanied by "prudent fiscal policies" in some cases. They highlight specific cases, such as Brazil, where progressive fiscal interventions and targeted social policies were instrumental in reducing the Gini index from over 60 in 1990 to 53.5 by 2019, despite market pressures. Additionally, their analysis of 'Shared Socioeconomic Pathways' (SSPs) suggests that future inequality trends will be determined largely by the inclusiveness of social policies rather than market forces alone. Consequently, omitting these fiscal variables from an analysis of trade and inequality could lead to significant omitted variable bias.

Furthermore, the literature on technological drivers has evolved from skill-biased change to the impact of automation and artificial intelligence. Acemoglu (2024) posits that current technological waves—specifically generative AI and automation—are now the dominant forces altering labor demand. He argues that these technologies are displacing routine tasks performed by low- and middle-skilled workers while complementing high-skilled labor, thereby widening the wage gap more pervasively than trade exposure.

2.3 Methodological Approaches

In the analysis of time-series data, especially for the dynamic feedback among variables, researchers typically choose between univariate models (such as ARIMA) and multivariate frameworks (such as VAR).

Standard univariate models, including AutoRegressive Integrated Moving Average (ARIMA), are widely used for forecasting a single variable based on its own past values. However, the major limitation of ARIMA is that it treats variables in isolation. For this study, using a univariate approach would be insufficient because it cannot capture how external structural factors—specifically trade openness and fiscal policy—influence income inequality.

Hence, to address this limitation, this study adopts the Vector Autoregression (VAR) framework proposed by Sims et al. (1990). The VAR model is superior for this research because it is a multivariate system that treats all variables as endogenous. This allows us to examine the bidirectional feedback loops between trade and inequality. Furthermore, to analyze the transmission mechanism of economic shocks, we utilize Impulse Response Functions (IRFs) derived from the VAR system. As elucidated by Stock and Watson (2001), IRFs are the primary tool for structural analysis, allowing researchers to isolate the effect of a specific shock to one variable on the time path of another variable while holding other shocks constant.

3 METHODOLOGY AND DATA ANALYSIS

3.1 Variable selection

To investigate the impact of trade openness on inequality, we utilize annual data for the United States covering the period from 1972 to 2023. Following the literature on distributional analysis (Musgrave and Musgrave, (1989); Garcia Rojas et al., (2025)), we select four endogenous variables to capture the interaction between market forces and government redistribution.

Trade Openness

In order to measure the trade openness of the U.S., the trade openness indicator is taken into consideration. The variable represents the percentage of the sum of export and import amounts in the GDP.

Gini index (Gini coefficient)

This study utilizes the Gini coefficient as the dependent variable to quantify income inequality. Originally developed by Gini (1912), this index measures the extent to which the distribution of income within an economy deviates from a perfectly equal distribution. Methodologically, the coefficient is derived from the Lorenz Curve, calculated as the ratio of the area between the line of perfect equality and the observed income distribution curve. In this analysis, the index is expressed as a percentage ranging from 0 (perfect equality) to 100 (maximum inequality).

Tax revenues and government spending

To ensure the robustness of the model and mitigate potential omitted variable bias, Tax Revenue and Government Spending (as % of GDP) are included as control variables. According to Musgrave and Musgrave (1989), fiscal policy is the most direct instrument for income redistribution via the 'tax-transfer scheme'. Specifically, while taxation extracts resources from high-income groups, government spending reallocates them to lower-income households through subsidies and public services.

The summaries of variable definitions, measurement units, and data sources utilized in this study are depicted in Table 1. In addition, to ensure consistency and reliability, all data in this paper is sourced from reputable international databases, including the World Bank and the Federal Reserve Economic Data (FRED).

Table 1: Variables and Data Sources

Variables	Notations	Unit	Source and Notes
Gini index	gini	%	World Development Indicator
Trade openness	trade	%	World Bank Indicator
Tax revenues (% GDP)	tax	%	FRED*
Government spending (% GDP)	spend	%	FRED*

Note: * denote Federal Reserve Economic Data, Federal Reserve Bank of St. Louis.

[Table 2](#) presents the descriptive statistics for the observed variables over the 1972–2023 period. The Gini index has a mean of 39.13% with a standard deviation of 2.29%, fluctuating between a minimum of 34.70% and a maximum of 41.90%. Trade openness averages 22.32% but shows significant volatility (Std. Dev. = 4.90%). Regarding fiscal policy, Government spending (mean = 14.42%) is on average higher and more volatile (Std. Dev. = 2.60%) than Tax revenues (mean = 10.89%; Std. Dev. = 1.03%)

Table 2: Summary statistics of variables

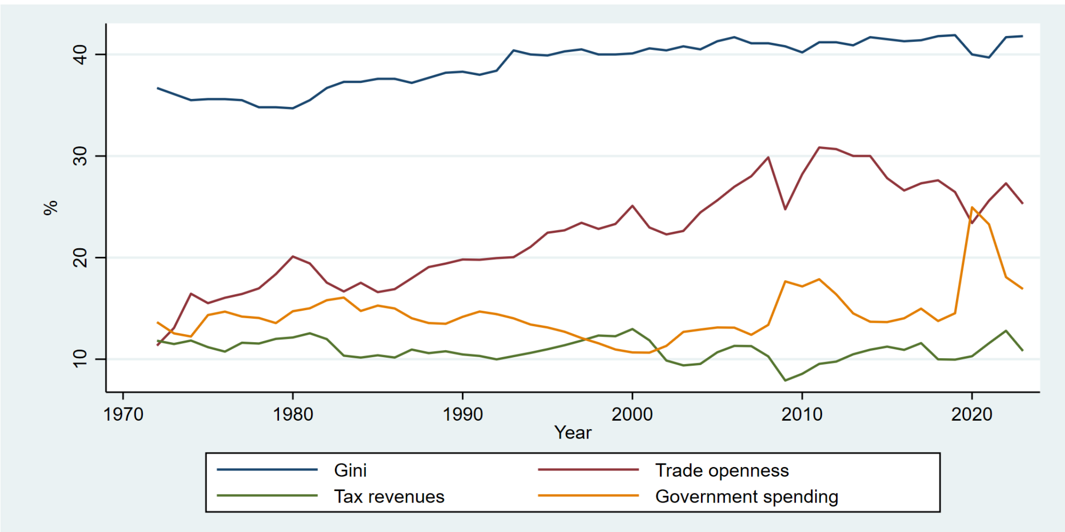
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Gini index	52	39.133	2.286	34.700	41.900
Trade openness	52	22.320	4.900	11.341	30.842
Tax revenues (% GDP)	52	10.891	1.028	7.904	12.971
Government spending (% GDP)	52	14.419	2.604	10.646	24.950

3.2 Model specification

Figure 1 visualizes the evolution of the Gini index, trade openness, tax revenue, and government spending in the U.S. economy from 1972 to 2023. The Gini index exhibits a persistent upward trend, rising from approximately 36% in the early 1970s to over 41% in recent years, signaling an increase in income inequality over the last five decades. Similarly, Trade Openness shows a long-term increasing trend, reflecting the deepening integration of the U.S. into the global economy, although it displays higher volatility with noticeable dips during the 2008 Global Financial Crisis and the onset of the COVID-19 pandemic.

Regarding fiscal policy, tax revenue remains relatively stable, hovering around 10-12%. In contrast, public spending exhibits counter-cyclical behavior, with a dramatic spike observed in the 2020–2021 period, corresponding to the massive fiscal stimulus packages implemented in response to the COVID-19 shock.

Figure 1: The movements of Income equality, Trade openness, Tax revenues, and Government spending in the U.S. from 1972 - 2023



3.2.1 Unit root tests

Firstly, the stationarity of the time series was tested using the Augmented Dickey-Fuller (ADF) test Said and Dickey (1984). The results, as shown in (Table 3), indicate that all variables are non-stationary at levels but become stationary at first difference (I(1)) at the 1% significance levels.

Table 3: ADF test for stationarity or unit root tests

	ADF (t-statistic)	
Variables	**Data (at level)**	**Data (first difference)**
Gini index (gini)	-0.938	-6.884^{***}
Trade openness (trade)	-2.253	-7.330^{***}
Tax revenues (tax)	-3.115^{**}	-5.626^{***}
Government spending (spend)	-2.695^{*}	-6.533^{***}

Note: *, ** and *** denote statistical significance at 10%, 5% and 1%.

3.2.2 VAR model

The primary objective of this study is to analyze the dynamic interdependencies between trade, fiscal policy, and inequality without imposing a priori structural restrictions. We employ a Vector Autoregressive (VAR) model (Sims et al., 1990). The reduced-form VAR model of order p is specified as follows:

$$X_t = \alpha + A_1 X_{t-1} + A_2 X_{t-2} + ... + A_p X_{t-p} + \epsilon_t$$

where X_t is the vector of endogenous variables (Gini index, Trade openness, Tax revenues, Government spending); α is the vector of intercepts; the As are the coefficient matrices. Finally, ϵ_t is a vector of error terms, which are assumed to be serially uncorrelated.

Although standard econometric textbooks often suggest differencing non-stationary variables (I(1)) to achieve stationarity, we elect to estimate the VAR model in levels. This decision is grounded in the influential work of Sims et al. (1990), who demonstrated that even when variables are non-stationary and not cointegrated, the estimators in a level VAR are consistent for Impulse Response Functions (IRF).

3.2.3 Lag length criteria

To determine the optimal lag order (p) for the VAR model specified above, we evaluated standard information criteria including the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), and Schwarz Bayesian Information Criterion (SBIC). Table 4 presents the results.

While the SBIC and HQIC suggest a more parsimonious model with 1 lag, the AIC, FPE, and LR tests all indicate that a lag order of 3 is optimal (AIC = 11.2795). In this study, the AIC information standard is preferred to ensure the model is sufficiently flexible to capture the delayed effects of fiscal and trade policy shocks on inequality. Consequently, the model is estimated as a VAR(3).

Table 4: Lag length selection criteria

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	-394.423		190.464	16.6009	16.6599	16.7569
1	-253.888	281.07	1.06558	11.412	11.7066*	12.1917*
2	-239.369	29.037	1.15048	11.4737	12.0041	12.8771
3	-218.707	**41.325***	**0.98352***	**11.2795***	12.0455	13.3066
4	-206.015	25.384	1.21416	11.4173	12.4191	14.0682

Notes: * indicates the optimal number of lags according to the respective criteria.

3.2.4 Cointegration test

To determine the appropriate modeling framework, we conducted the Johansen cointegration test. The results, reported in Table A1 (Appendix A), indicate a cointegration rank of zero, meaning the null hypothesis of no cointegration cannot be rejected at the 5% significance level. The absence of a long-run cointegrating relationship implies that a Vector Error Correction Model (VECM) is not required. Therefore, we proceed with the Unrestricted Vector Autoregression (VAR) model to analyze the short-term dynamics and impulse response functions.

3.2.5 Model Diagnostics

To ensure the statistical reliability of the estimated VAR model, we conducted a comprehensive set of diagnostic tests focusing on stability, residual autocorrelation, and causal relationships.

First, the stability of the VAR system was visually verified. As illustrated in Figure B1 (Appendix B), all inverse roots of the AR characteristic polynomial lie inside the unit circle. Since no root lies on or outside the boundary (i.e., with the largest modulus being 0.928), the model satisfies the stability condition.

Second, the Lagrange Multiplier (LM) test was employed to check for residual serial correlation. The results in Table A2 (Appendix A) indicate that we cannot reject the null hypothesis of no autocorrelation at the 5% significance level for both lag order 1 (p = 0.628) and lag order 2 (p = 0.901). This confirms that the selected lag length is appropriate for the model since the residuals are white noise.

Finally, to examine the dynamic interactions within the system, we performed Granger causality tests, which evaluate the null hypothesis that the estimated coefficients on the lagged values of the explanatory variables are jointly zero (Granger, 1969). As reported in Table A3 (Appendix A), regarding the income inequality (Gini) equation, while the Wald tests fail to reject the null hypothesis for individual macroeconomic variables (trade, tax, spend), the test significantly rejects the null hypothesis for the variables as a group ($\chi^2 = 19.55, p = 0.021$). This result suggests that trade openness and fiscal policy variables jointly Granger-cause income inequality, confirming that they possess significant predictive power when considered collectively. Furthermore, the results reveal significant interactions among other variables in the system. Notably, tax revenue is found to significantly Granger-cause trade openness ($p < 0.01$). This evidence of interdependence confirms that the variables form a complex system, thereby justifying the use of a multivariate VAR framework instead of analyzing them in isolation.

4 IMPULSE RESPONSE FUNCTION

4.1 Impulse response function

The objective of the dynamic relationships between variables in this paper is exhibited via computing the impulse response function (IRFs). Figure 2 shows the reaction of the Gini index, Government Spending, Tax revenues, and Trade openness to a 1% shock in Trade openness, which is the main objective; other IRFs can be found in Figure B2, Figure B3, Figure B4. The result suggests that with a 1% increase in Trade openness, the Gini index has no significant reaction, as same for Tax revenues. Whereas, Government spending has a significant instant reaction, which means in the short term (i.e., lag 0-2), Government spending dropped and gradually increased back to 0. In the long term (from lag 6-8), the spending variable only slightly increases.

Figure 2: IRF to a 1% of trade shock

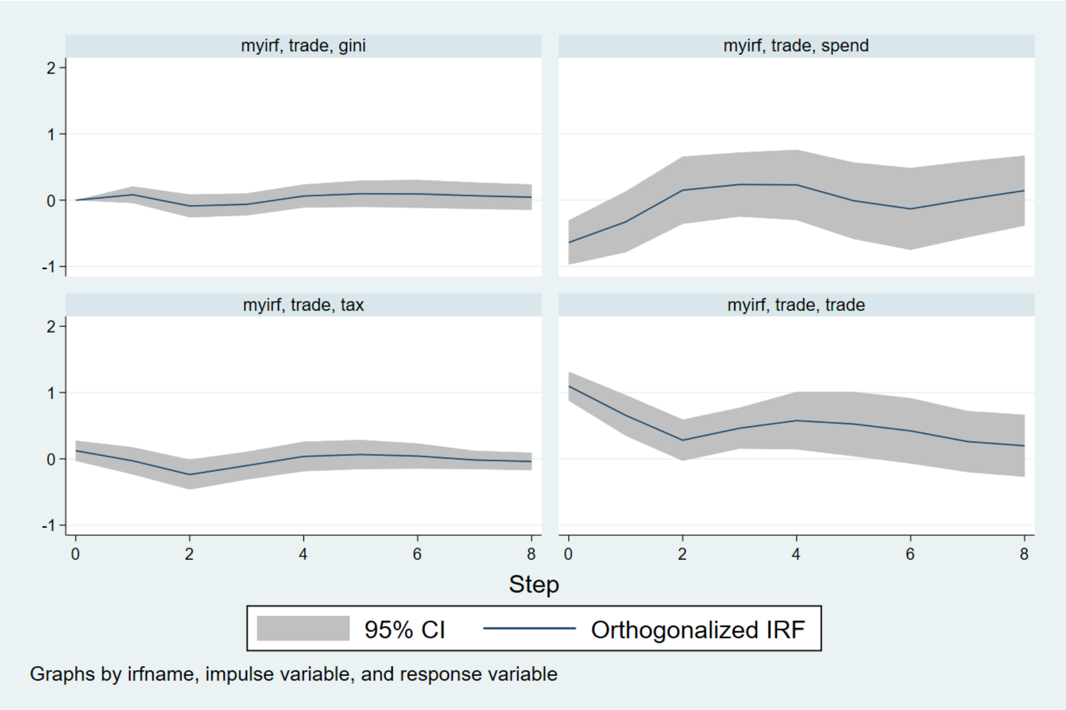


Table 5 illustrates the numerical reaction of variables to the shock of Trade openness.

Table 5: The response to a 1% Trade Shock

Variables	Impact	1y	2y	3y	4y	5y	6y
Gini index	0.000	0.082	-0.086	-0.062	0.062	0.097	0.095
Trade openness	**1.097**	**0.656**	0.281	**0.463**	**0.577**	**0.525**	0.422
Tax revenues	0.123	-0.029	**-0.236**	-0.101	-0.036	0.066	0.042
Government spending	**-0.638**	-0.326	0.151	0.236	0.230	-0.008	-0.130

Notes: Bold numbers indicate significance at the 5% confidence level.

The null-hypothesis of this study is the significant dynamic response of the Gini index to a 1% shock in Trade openness; however, the result rejects the hypothesis. Instead, IRFs of Trade openness shocks predict a significant linkage between Trade openness and Government spending. That negative immediate response of Government spending (-0.638 at 5% significance level) indicates the development of the economy, driven by a rise in trade volume, leads to a decrease in Government spending, which provides evidence for the counter-cyclical fiscal policy in the U.S.

4.2 Discussion

As shown in Figure 1, Gini exhibits a persistent trend, while Government Spending has a cyclical fiscal stance. These movements may imply the property of consistency in sociology indicators (i.e., Gini) with a high tendency and the sensitivity of economic factors to the shocks of an economic situation. Although the insignificant response of the Gini index contradicts the theory of Stolper and Samuelson (1941), this finding aligns with previous U.S. studies, such as Lawrence (2008) and Krugman (2008). These authors argue that trade plays a minor role in rising inequality compared to technological changes, as trade volumes are insufficient to drive the aggregate wage gap. Consequently, our results reinforce the perspective that trade openness is not the primary determinant of income inequality in the U.S..

The review by Harrison et al. (2011) summarizes some potential reasons for the inconsistency of empirical work with the HO framework[4], and that simple approach is a guide to the trade and inequality problem, but requires more qualifications when it comes to the real world. In the empirical work part of the summary paper (Harrison et al., 2011), authors also highlight the incomplete understanding when ignoring the assumptions of the framework, such as perfect competition, free trade, and factor mobility[5]. Consequently, the classical framework does not account for the non-tradable goods and services, and the offshoring situation. As demonstrated by Feenstra and Hanson (1999), the reallocation of task-abundance responsibilities between involved countries increases wages in both countries[6].

Our findings offer a nuanced perspective when compared to the influential work of Autor et al. (2013). Their study, focusing on local labor markets specifically exposed to the 'China Shock,' found that import competition significantly harmed low-skilled labor and exacerbated inequality in those specific manufacturing-heavy regions. In contrast, our study employs a macro-level VAR approach to examine the aggregate dynamics of the entire U.S. economy.

The fact that our study finds no statistically significant response of the national Gini coefficient to trade shocks suggests that while trade may produce concentrated losses in specific sectors or regions (as identified by Autor et al. (2013)), these effects do not necessarily translate into a deterioration of overall national income distribution. This distinction provides a positive signal for policymakers. It implies that the classic trade-off

[4] Stolper-Samuelson model is one of the implications of Heckscher-Ohlin model

[5] Not allow for "immigration" of factors of production (i.e., capital and labour)

[6] "Offshoring increases the relative demand for skilled labor in both countries involved because the offshored tasks are more skill intensive than those previously performed in the country to which they were offshored, but they are less skill intensive than those in the country that is doing the offshoring"(Harrison et al., 2011)

between economic openness and equity may be less severe at the aggregate level than previously feared. Consequently, policymakers can pursue trade liberalization to foster growth, provided that they implement targeted safety nets for specific affected areas, without being paralyzed by the dilemma that open trade inevitably worsens nationwide inequality.

5 CONCLUSION

5.1 Summary

This study empirically examined the dynamic relationship between trade openness and income inequality in the United States over the period from 1972 to 2023. To ensure a robust analysis and address the omitted variable bias, this paper incorporated fiscal policy variables (tax revenue and government spending) into a Vector Autoregression (VAR) framework. This approach allows us to capture broader macroeconomic interactions that simpler models might overlook.

The empirical results derived from the Impulse Response Functions (IRFs) lead to two primary conclusions. First, contrary to the predictions of the Stolper-Samuelson theorem, we found no statistically significant response of the Gini index to shocks in trade openness. This finding aligns with the "technology-driven inequality" hypothesis supported by Lawrence (2008) and Krugman (2008). Second, the study reveals a significant interaction between trade and fiscal policy. Specifically, a positive shock to trade openness leads to an immediate and significant decline in government spending. This provides evidence of counter-cyclical fiscal behavior (or automatic stabilizers), implying that trade expansion often coincides with economic growth periods, thereby reducing the government deficit.

In conclusion, our findings suggest that while trade openness plays a crucial role in influencing U.S. fiscal dynamics, it is not the primary driver of the rising aggregate income inequality observed over the past five decades.

5.2 Limitations

Despite these findings, this study has some limitations that need to be taken into consideration. Firstly, the observed time period is from 1972 to 2023 (51 years), though the data is enough to conduct testing, the limited size of the data sample may be inefficient to draw conclusions for the whole population. Secondly, since Gini is a surveyed index, it may have bias in the way of conducted (including the answers from the respondents). In addition, Gini is an indicator that represents income equality; therefore, it cannot reflect all equality features, gender equality, for instance. Furthermore, Trade openness variable data in this study is just the monetary value of trading goods and services; thus, it does not separate the de facto and de jure (Grabner et al., 2020)[7] measurements among trade openness levels. Lastly, the Vector Autoregressive (VAR) model is sensitive to the lag length selection; though we have clarified the selection, there is still potential effect that may lead to incorrect in IRFs results.

[7] In brief, de facto stands for the actual flows of trade, including financial flows. De jure measures trade openness by evaluating trade-related policies/restrictions

Data Availability

The time-series data (1972–2023) used in this study, including the Gini index, trade openness, and fiscal policy indicators, were compiled from the World Bank's World Development Indicators and the Federal Reserve Economic Data (FRED). All datasets and the STATA code used for the VAR(3) estimation, unit root tests, and IRF generation are available for replication at: GitHub: trmuba2502/Time-Series-Econometrics

AI Declaration

In this work, we used Gemini in order to find the LaTeX code for formatting purpose. Also, since English is not our first language, we utilize Gemini for grammar correction.

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Appendix A: Tables

Table A1: Johansen tests for cointegration

Trend: Constant				Number of obs = 49	
Sample: 1975 thru 2023				Number of lags = 3	
Maximum rank	**Params**	**LL**	**Eigenvalue**	**Trace statistic**	**Critical value (5%)**
0	36	-242.47665	.	42.2177*	47.21
1	43	-227.45172	0.45842	12.1679	29.68
2	48	-224.6637	0.10756	6.5918	15.41
3	51	-222.56718	0.08201	2.3988	3.76
4	52	-221.36779	0.04778		

Note: * indicates the selected rank.

Table A2: Lagrange-multiplier test for Autocorrelation

lag	chi2	df	Prob > chi2
1	13.6036	16	0.62822
2	9.2907	16	0.90096

Note: H_0: no autocorrelation at lag order.

Table A3: Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
gini	trade	3.0724	3	0.381
gini	tax	2.397	3	0.494
gini	spend	6.1552	3	0.104
gini	ALL	19.547	9	0.021
trade	gini	2.2508	3	0.522
trade	tax	13.569	3	0.004
trade	spend	6.9031	3	0.075
trade	ALL	31.948	9	0.000
tax	gini	3.0891	3	0.378
tax	trade	8.4465	3	0.038
tax	spend	5.1162	3	0.163
tax	ALL	28.281	9	0.001
spend	gini	.7777	3	0.855
spend	trade	5.889	3	0.117
spend	tax	23.73	3	0.000
spend	ALL	26.85	9	0.001

Note: H_0: the estimated coefficients on the lagged values are jointly zero.

Table A4: The response to a 1% Tax Shock

Variables	**Impact**	**1y**	**2y**	**3y**	**4y**	**5y**	**6y**
Gini index	0.000	-0.008	0.083	0.071	-0.108	-0.142	-0.050
Trade openness	0.000	-0.003	-0.062	-0.516	**-0.868**	**-0.631**	-0.315
Tax revenues	**0.535**	**0.528**	**0.409**	0.048	-0.254	-0.223	-0.077
Government spending	0.071	-0.023	**-0.701**	-0.341	0.317	0.601	0.515

Notes: Bold numbers indicate significance at the 5% confidence level.

Table A5: The response to a 1% Government Spending Shock

Variables	**Impact**	**1y**	**2y**	**3y**	**4y**	**5y**	**6y**
Gini index	0.000	-0.057	0.057	0.063	-0.078	-0.099	-0.058
Trade openness	0.000	-0.065	0.155	-0.118	-0.314	-0.187	-0.096
Tax revenues	0.000	-0.062	-0.004	-0.125	-0.228	-0.147	-0.056
Government spending	**1.095**	**1.043**	**0.529**	**0.618**	**0.749**	**0.743**	0.650

Notes: Bold numbers indicate significance at the 5% confidence level.

Table A6: The response to a 1% Gini Shock

Variables	**Impact**	**1y**	**2y**	**3y**	**4y**	**5y**	**6y**
Gini index	**0.488**	**0.506**	**0.279**	**0.212**	**0.298**	**0.337**	**0.301**
Trade openness	0.039	-0.067	-0.106	0.240	**0.560**	**0.610**	0.506
Tax revenues	-0.085	-0.185	-0.235	-0.066	0.114	0.141	0.067
Government spending	**-0.529**	**-0.628**	-0.217	-0.379	-0.614	-0.635	-0.403

Notes: Bold numbers indicate significance at the 5% confidence level.

Appendix B: Figures

Figure B1: VAR Stability Condition

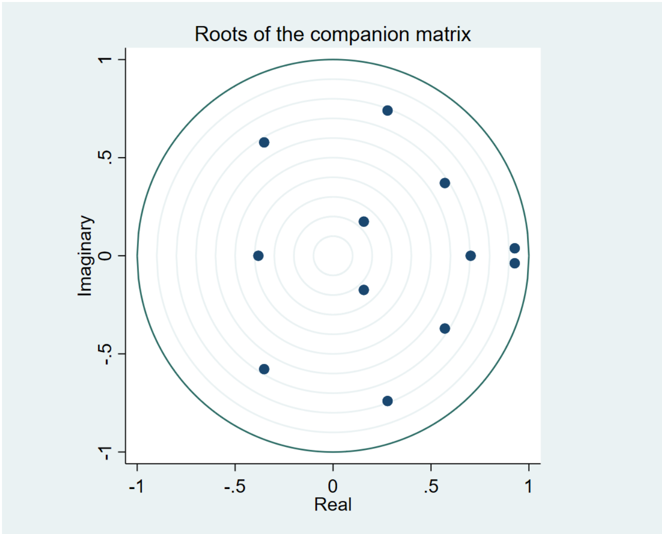

Figure B2: IRF to a 1% of tax shock

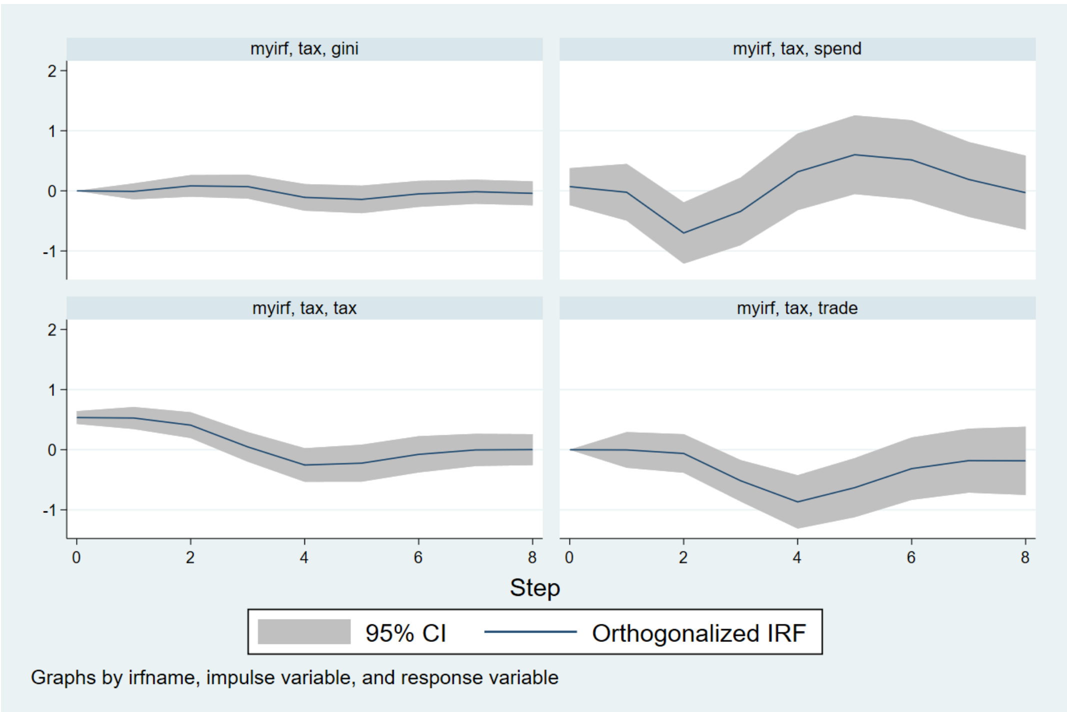

Figure B3: IRF to a 1% of spend shock

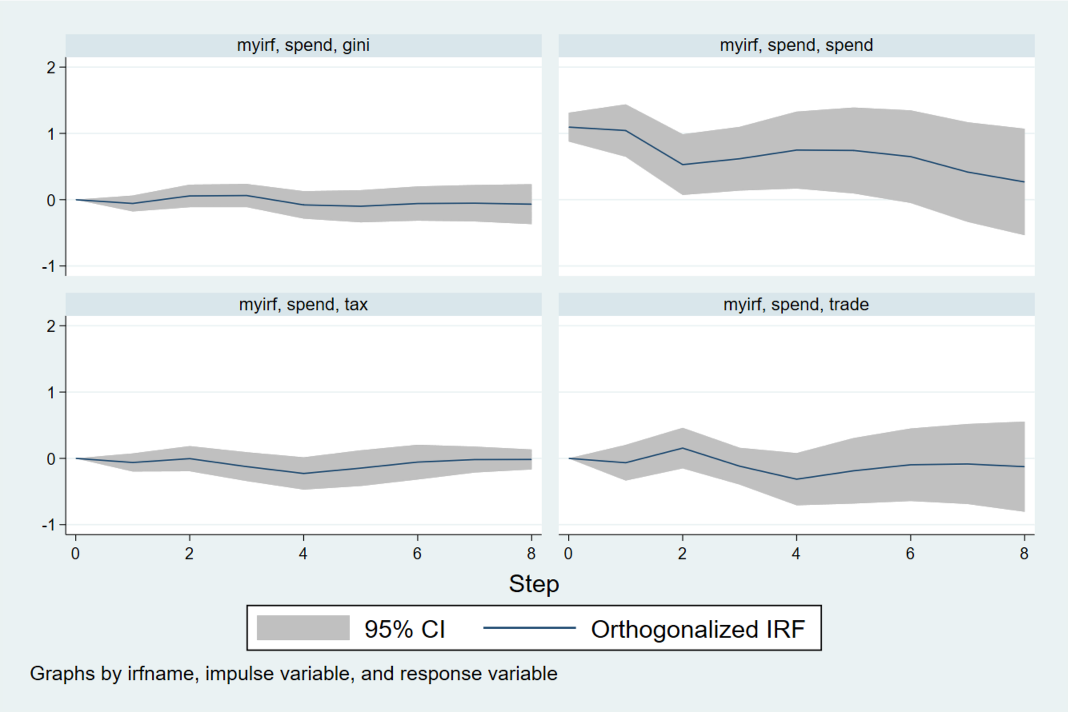

Figure B4: IRF to a 1% of gini shock