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

Duong Thi Nhu Y FAECIU23046  
Duong Hanh Trang FAECIU23029

Department of Economics, Finance, and Accounting  
Time Series Econometrics - Final Project Proposal

**Supervisor:**

Ph.D Do Hoang Phuong  
Date: January 2026

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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 ([Ricardo, 1817](#)). In addition, the break in the global chain due to COVID-19, or Donald Trump's ideology of MAGA<sup>1</sup>, once again raising up the world "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, 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. Governments use taxation and spending to redistribute income and mitigate inequality. 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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\*International University - VNUHCM

<sup>1</sup>Making America Great Again

## 2 LITERATURE REVIEW

### 2.1 Theory Framework

Aligned with trade liberation, the problem of protecting the equality in income distribution among the countries has also been brought by [Stolper and Samuelson \(1941\)](#)<sup>2</sup>. 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 applicability of the Stolper and Samuelson theorem about the income disparity in the U.S.'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.

When looking at the U.S. specifically, there is 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.

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.

Furthermore, the role of fiscal policy—specifically taxation and government spending—remains central to modern distributional analysis. [Garcia Rojas et al. \(2025\)](#) provide strong empirical evidence from the 1990–2019 period demonstrating that economic growth alone is insufficient to reduce inequality unless accompanied by 'prudent fiscal policies'. 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

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<sup>2</sup>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.

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, as fiscal consolidation often occurs simultaneously with trade liberalization reforms.

### 2.3 Methodological Approaches

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

Standard univariate models like ARIMA (AutoRegressive Integrated Moving Average) 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.

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 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

#### 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.

Table 1 summarizes the variable definitions, measurement units, and data sources utilized in this study. To ensure consistency and reliability, all time-series data are 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 (ranging from 11.34% to 30.84%). Regarding fiscal policy, Government Spending (mean: 14.42%) is consistently higher and more volatile than Tax Revenue (mean: 10.89%).

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

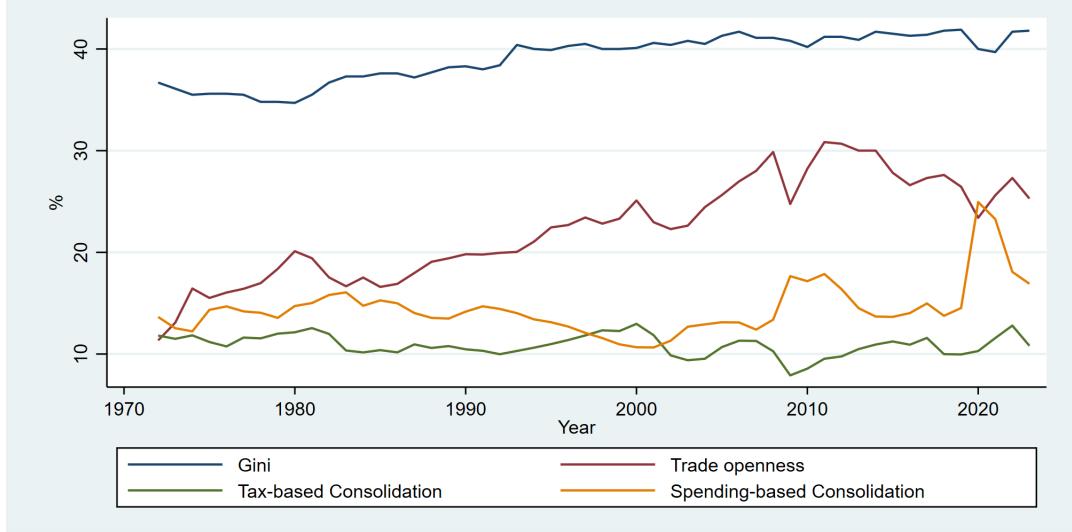
### 3.2 Model specification

Figure 1 visualizes the evolution of the Gini index, trade openness, tax-based consolidation, and spending-base consolidation 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 a structural 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-based consolidation remains relatively stable, hovering around 10-12%. In contrast, Spending-based consolidation 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-based consolidation, and Spending-based consolidation in the U.S. from 1972 - 2023



### 3.2.1 Unit root tests

We examined the stationarity of the time series using the Augmented Dickey-Fuller (ADF) test [Said and Dickey \(1984\)](#) (Table 3). The results indicate that all variables—Gini index, Trade Openness, Tax-based Consolidation, and Spending-based Consolidation—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

Variables	ADF (t-statistic)	
	Data (at level)	Data (first difference)
Gini index (gini)	-0.938	-6.884***
Trade Openness (trade)	-2.253	-7.330***
Tax-based Consolidation (tax)	-3.115**	-5.626***
Spending-based Consolidation (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:

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

where  $X_t$  is the vector of endogenous variables (Gini index, Trade Openness, Tax-based Consolidation, Spending-based Consolidation);  $\alpha$  is the vector of intercepts; the  $A_s$  are the coefficient matrices. Finally,  $\epsilon_t$  is a vector of error terms, which are assumed to be serially uncorrelated.

### 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). We prioritize the AIC in this study to ensure the model is sufficiently flexible to capture the delayed effects of fiscal and trade policy shocks on inequality. Consequently, we estimate the model 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	<b>41.325*</b>	<b>0.98352*</b>	<b>11.2795*</b>	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 strictly inside the unit circle. Since no root lies on or outside the boundary (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 residuals are white noise and that the selected lag length is appropriate for the model.

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. Moreover, significant feedback loops are observed elsewhere in the system—notably with fiscal variables Granger-causing trade openness ( $p < 0.01$ )—which underscores the interconnectedness of the variables and justifies the adoption of a multivariate VAR framework rather than isolated univariate analyses.

#### 4 IMPULSE RESPONSE FUNCTION

Figure 2: IRF to a 1% of trade shock

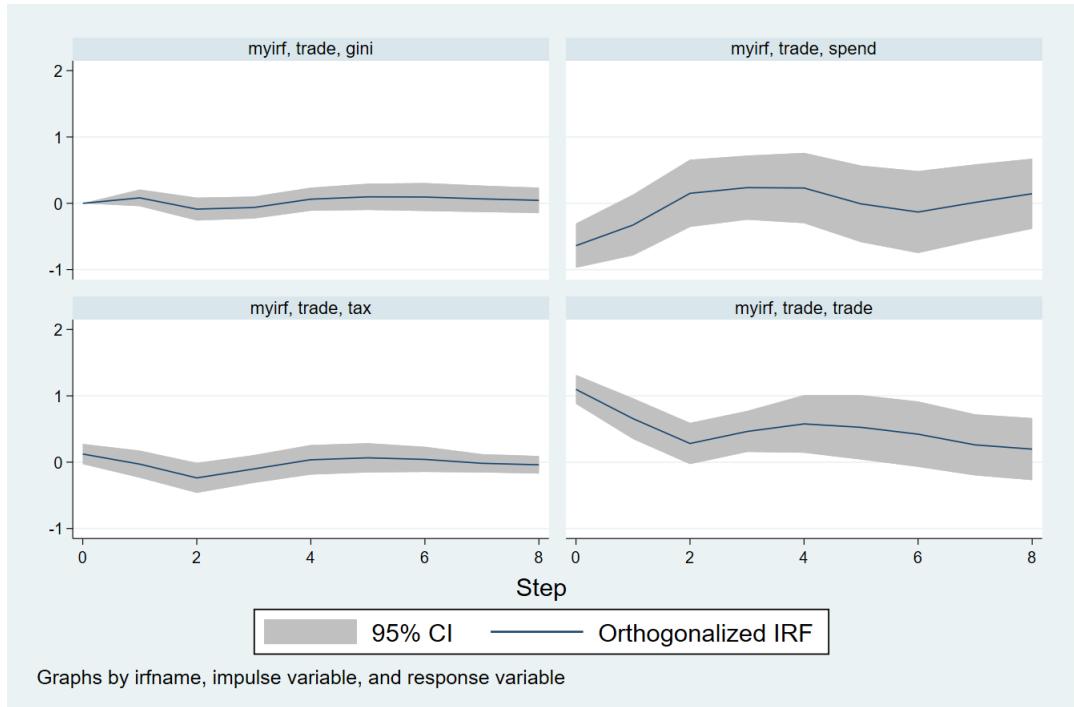


Table 5: The response to a 1% Trade Shock

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	<b>1.097</b>	<b>0.656</b>	0.281	<b>0.463</b>	<b>0.577</b>	<b>0.525</b>	0.422
Tax-based consolidation	0.123	-0.029	<b>-0.236</b>	-0.101	-0.036	0.066	0.042
Spending-based consolidation	<b>-0.638</b>	-0.326	0.151	0.236	0.230	-0.008	-0.130

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

## 5 CONCLUSION

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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	<b>-0.868</b>	<b>-0.631</b>	-0.315
Tax-based consolidation	<b>0.535</b>	<b>0.528</b>	<b>0.409</b>	0.048	-0.254	-0.223	-0.077
Spending-based consolidation	0.071	-0.023	<b>-0.701</b>	-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-based consolidation	0.000	-0.062	-0.004	-0.125	-0.228	-0.147	-0.056
Spending-based consolidation	<b>1.095</b>	<b>1.043</b>	<b>0.529</b>	<b>0.618</b>	<b>0.749</b>	<b>0.743</b>	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	<b>0.488</b>	<b>0.506</b>	<b>0.279</b>	<b>0.212</b>	<b>0.298</b>	<b>0.337</b>	<b>0.301</b>
Trade openness	0.039	-0.067	-0.106	0.240	<b>0.560</b>	<b>0.610</b>	0.506
Tax-based consolidation	-0.085	-0.185	-0.235	-0.066	0.114	0.141	0.067
Spending-based consolidation	<b>-0.529</b>	<b>-0.628</b>	-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

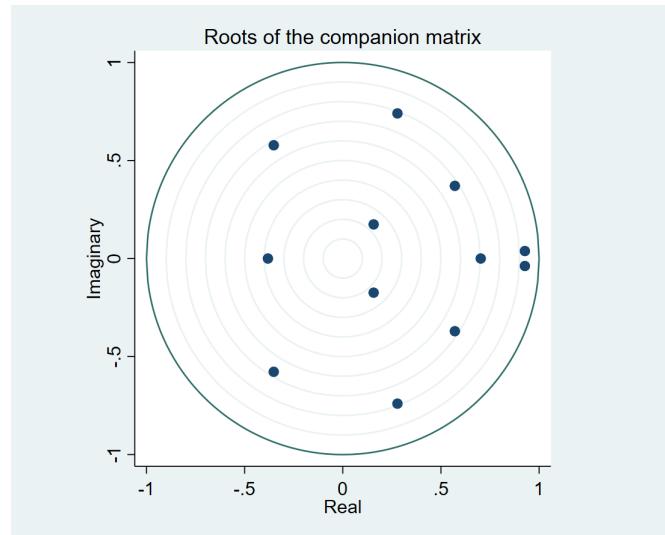


Figure B2: IRF to a 1% of tax shock

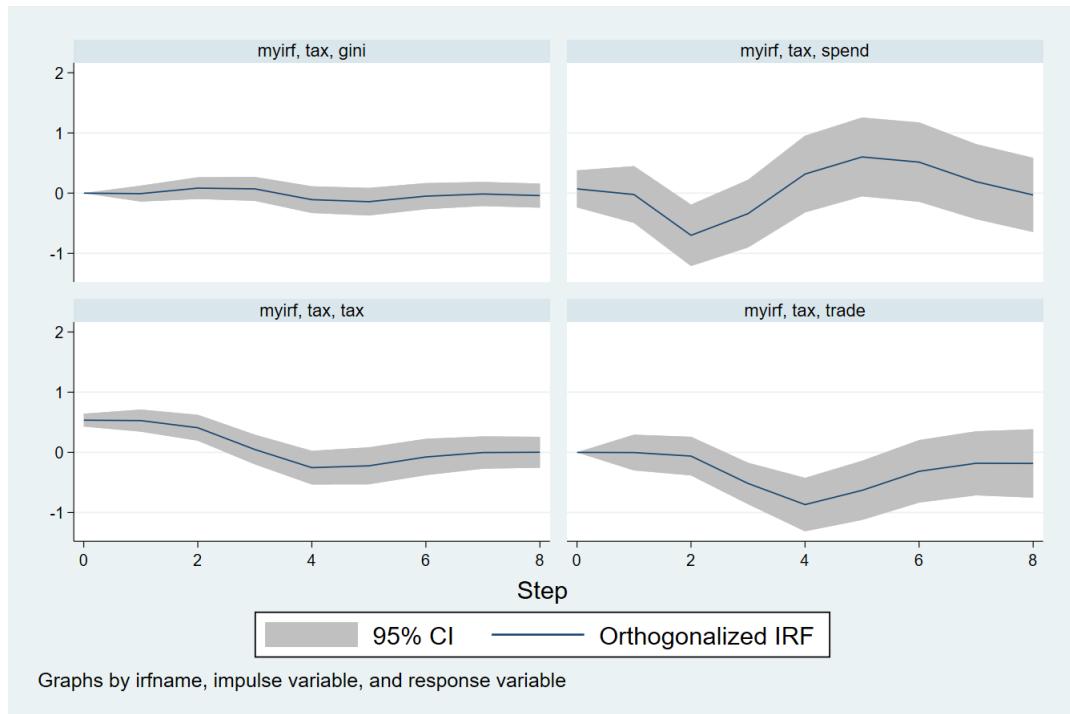


Figure B3: IRF to a 1% of spend shock

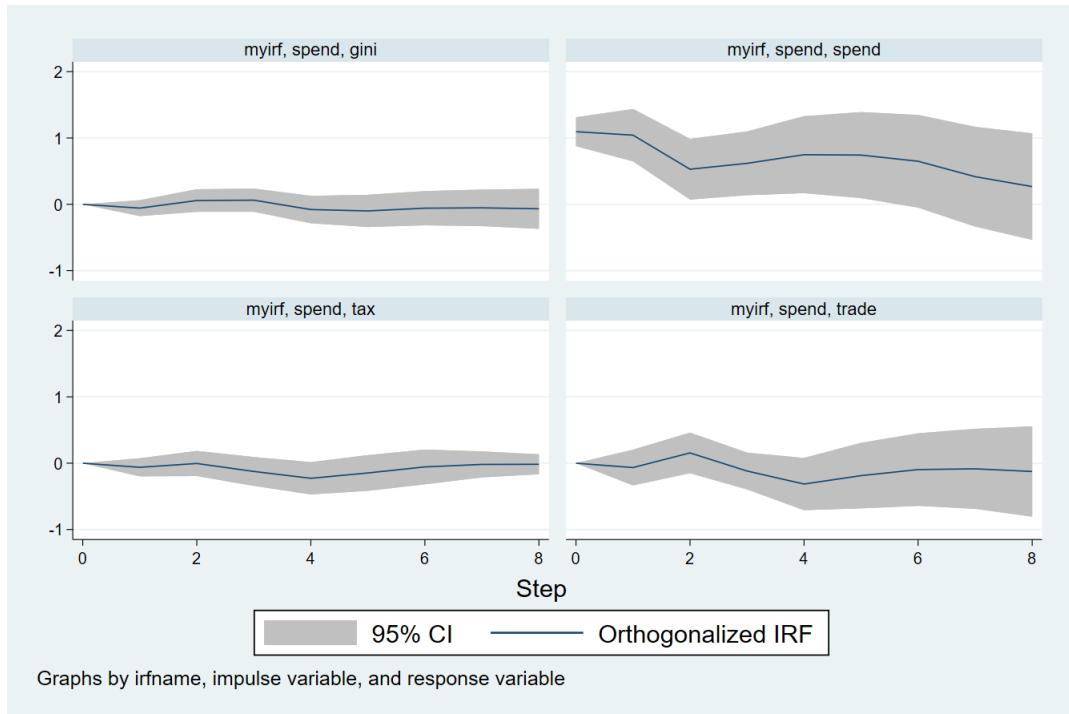


Figure B4: IRF to a 1% of gini shock

