THE CAUSAL NEXUS BETWEEN EMPLOYMENT, EXPORT, AND ECONOMIC GROWTH: EVIDENCE FROM THE USA

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1. INTRODUCTION

While the influence of exports on employment has been a focus of research for many years, it appears that the literature in this topic has yet to come to a consensus, and the link between exports and employment remains unclear. Since the end of World War I, the USA government has been searching for a global market free of trade restrictions. Companies involved in mass production promoted the liberalization of international trade (Chase, 2009). The conventional economic knowledge holds that trade liberalization has two effects on the labor market. The conventional economic knowledge holds that trade liberalization has two effects on the labor market. The first is related to imports and suggests that a company facing import competition may undergo market shrinkage or exit from the market causing workers to lose their jobs. Alternatively, a company that has participated in foreign trade may contribute to the labor market by expanding and creating new business lines (Feenstra et al., 2019).

However, many studies have been undertaken on the effects of international trade on the labor force, there are much less on the effects of exports alone. While it is believed that entering foreign markets would boost employment, domestic supply shocks induced by the development of new technologies and the rise in total factor productivity are anticipated to reduce employment and increase exports (Feenstra et al., 2019). Increases in a country's labor productivity, that is, one unit of labor production, may result in a decline in labor demand, even if exports rise (Sasahara, 2019).

After 1980, several developing nations opened their economies to the world and engaged in international trade. It has led to a shift in the quantity demanded of unskilled and skilled labor in favor of skilled ones (Charfeddine & Mrabet, 2015). While the traditional theory of international trade demonstrates that exports enhance employment (Chen & Chen, 2014), the new trade theory asserts that exports may have a neutral or even negative impact on job creation. It varies based on the characteristics of each individual. Individual variables, such as gender may influence the outcome. According to new theories of international trade, exports might lower employment for the following reasons: The exporting firms' export trade screening mechanism may result in a decrease in the number of recruited individuals and increased exports improve the quality of labor forces while reducing the employment rates of low- and middle-skilled workers (Chen et al., 2017). New trade theories diverge from traditional trade theories since they include labor market imperfections into their theoretical models and reject assumptions that are impossible to attain in reality, such as perfect competition and full employment (Akcoraoglu & Acikgoz, 2011).

In this book chapter, in addition to examining the link between exports and employment by concentrating on bidirectional causality rather than one-way causality, the economic growth variable was also included in the model. The aim of this book chapter is examining the causal relationship between employment, exports, and economic growth in the USA from 1990 to 2019. The estimation results are analyzed using the Johansen cointegration

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test, the Granger causality test based on the vector error correction model (VECM), the impulse-response function, and variance decomposition. One of the chapter's key goals is to establish the short- and long-term effects of exports and economic growth proxied by GDP on employment. Employment is therefore considered as an endogenous variable. Exports, employment, and GDP data belonging to 1990-2019 period are collected from World Bank. The USA was chosen for the analysis since it is one of the most developed exporting countries in the world, and the time interval is adjusted to encompass the 30 years preceding the last time data are available. The effects of the exports increase on employment were searched with the input-output analyses at the industrial or firm levels in many studies. This study measures the effect of exports on employment in USA by also using the GDP data as a proxy of the economic growth. In this book chapter the data were analyzed by using the methods of time series analysis.

The following sections comprise the remainder of the study: Section 2 conducts a brief review of the literature. Section 3 introduces the data sources and methodology utilized in the research. Section 4 summarizes the empirical research findings. The last section summarizes the findings and includes conclusion remarks.

2. LITERATURE REVIEW

A brief literature summary on the aim of this study is presented in Table 1.

Table 1. A Brief Literature Review

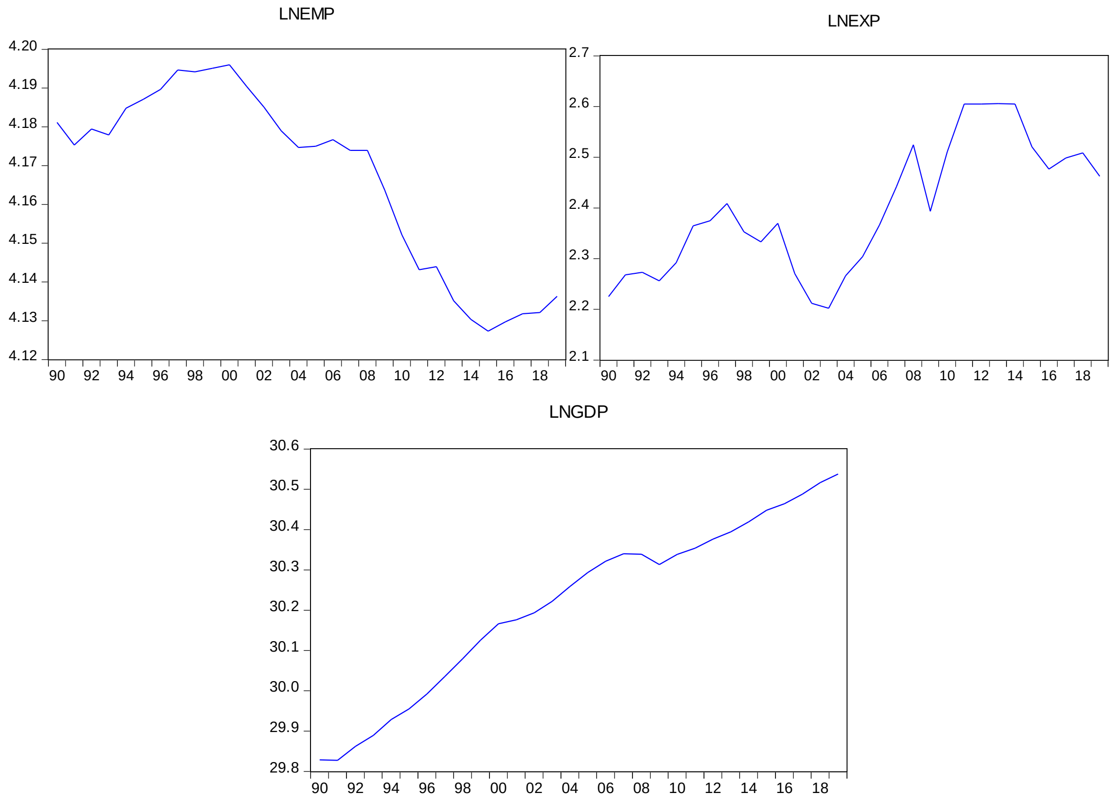
Authors and Year	Time Interval and Countries of Study	Methods	Results
Feenstra & Sasahara (2018)	1995-2011; U.S. imports and exports from China	Input – Output Analysis (I-O Analysis)	The expansion in exports of US raised manufacturing employment by 2 million, resource industries employment by 0.5 million, and service employment by 4.1 million. In total, it provided an employment increase of 6.6 million.
Feenstra, Ma & Xu (2019)	1991-2011; U.S. imports and exports from China	OLS- 2SLS	Export growth generates a significant growth in employment.
Sasahara (2019)	2000-2014; U.S., China, Japan	I-O Analysis	Export increases result in employment increases. Exports from industries with a higher level of domestic value added, including energy resources, textiles, and services, have a larger employment effect.
Lafuente, Vaillant & Moreno-Gómez (2018)	2008; Romanian small- and medium-sized businesses	Linear Regression Models	Exporting appears to be positively correlated with job creation. Whereas jobs growth is more evident among new exporters, firms that discontinue exporting report job losses.
Chen, Zhao & Yu (2017)	2005-2007; China	Unified Analysis such as System GMM Estimator, Difference-in Difference and PSM Estimation	The relationship between industrial firms' exports and employment levels of women is investigated. Female employment grows in proportion to the size and growth of a business's exports.
Fu & Balasubramanyam (2005)	1987-1998; 29 provinces of China	Two step GMM	Exports affect employment positively.
Chen & Chen (2014)	2006-2009; China	GMM Method	Increase in exports enhances employment.

Ko, Rangkakulnuwat & Paweenawat (2015)	1991-2012; ASEAN 5	Panel Data Analysis	Exports have been shown to have a negative impact on employment.
Jenkins (2004)	1995-1999; Vietnam	Panel Data Analysis	Export volume has a negative impact on employment.
Greenaway, Hine & Wright (1999)	1979-1991; UK	Panel Data Analysis	Exports affect employment negatively.

3. DATA AND METHODOLOGY

In this study, annual data of the USA covering the period 1990-2019 are used. The data used were collected from the World Bank World Development Indicators Data Base (WDI). Using data from the World Bank, Figure 1 depicts the time path graphs of the series in the USA between 1990 and 2019.

Figure 1. Change in Variables through Time (1990-2019)



The data are estimated to be nonstationary at level, as seen in Figure 1. Table 2 provides the definitions, sources, and summary statistics for the variables in the established model.

Table 2. Definitions of Variables, Data Sources and Summary Statistics

Variables	Definitions of Variables	Source of Variables	Number of Observations	Mean	Standard Deviation	Min.	Max.
lnemp	Exports of goods and services (% of GDP)	World Bank WDI	30	4.166989	0.023706	4.127296	4.195998
lnexp	Labor force participation rate, total (% of total	World Bank WDI	30	2.396524	0.127199	2.201999	2.605982

	population ages 15+) (modeled ILO estimate)						
lngdp	GDP (constant 2010 US$)	World Bank WDI	30	30.21616	0.217634	29.82730	30.53794

All variables were used in our study by taking their natural logarithms. Considering the literature, as the long-term effect of export on employment is expected to be positive according to traditional trade theories. The magnitude of this effect varies according to a country's employment structure, organizational structure of the workforce, cultural codes, public audits, and the duration and amount of unemployment payments.

The necessary steps for doing a time series analysis are listed below. The method is preferred to prevent producing spurious results and to detect relationships between the data.

3.1.Unit Root Tests

The determination of whether a time series is stationary or not is one of the critical stages of time series analysis. If the series are not stationary, classical regression analysis can produce spurious results. Utilizing unit root tests, stationarity of the series was initially confirmed. Stationarity analysis was carried out using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Ng-Perron unit root tests in this research. Whereas the ADF unit root test is frequently employed in studies, its power is fairly low for small samples (Zhang et al., 2019). Consequently, it was determined if subsequent unit root tests confirmed the ADF results. The results of the unit root tests are illustrated by taking the application of Köse and Ünal (2021) as an example, and Akaike Information Criterion (AIC) was preferred as stated in the aforementioned study.

3.2.VAR, Johansen Contegration and VEC Analysis

After determining that all variables are stationary at the I(1) level, VAR analysis was used to investigate short-term relationships and determine how the series were influenced by one another. The VAR analysis was performed to evaluate the effects of random disturbances on the system. With VAR analysis, the objective is to derive impulse-response functions and variance decomposition. The Johansen cointegration analysis was used to examine whether the variables had a long-term relationship (Zhu et al., 2019).

In this study, the direction and response rate of dynamic relationships between variables were conducted using impulse response function and variance decomposition analysis.

The equation (1) denotes the p-lagged VAR(p) model for k stationary time series.

$$\boldsymbol{y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + Bx_t + \varepsilon_t} \tag{1}$$

The term $\boldsymbol{y_t}$ refers to the $\boldsymbol{kx}1$-dimensional vector of endogenous variables, $\boldsymbol{x_t}$ denotes $\boldsymbol{dx}1$-dimensional vector of exogenous variables, $\boldsymbol{A_1,...,A_p}$ denotes $\boldsymbol{kxk}$-dimensional matrix of the coefficients of the lagged variables, B denotes $\boldsymbol{kxd}$-dimensional matrix of the coefficients of exogenous variables, and $\boldsymbol{\varepsilon_t}$ denotes the $\boldsymbol{kx}1$-dimensional vector of identically independently distributed error terms (Brahmasrene et al., 2014). The VAR model assumes that all variables are symmetrical and endogenous. The correct estimation of the lag length p is a crucial step in VAR analysis. The optimal lag length should be chosen in such a way that the model's residuals exhibit no autocorrelation, no heteroscedasticity, and normal distribution. If autocorrelation is observed, the model should be expanded by including the higher order lagged variable and the model should be tested again. The optimal lag order in the model can be determined using a variety of tests, including the LR (Likelihood), FPE

(Final Prediction Error), AIC (Akaike Information Criterion), SIC (Schwarz Information Criterion), and HQ (Hannan Quinn Information Criterion). Due to the fact that all variables are I(1) variable, the long-run relationship between them was investigated using the Johansen Cointegration test. Each series is considered endogenous in this methodology, and the cointegration connection is evaluated as a vector. Maximum likelihood procedure is used in this test. By taking the equation (1) as the time series vector, the error correction model (VECM) shown in equation (2) is obtained using equation (1):

$$\Delta \boldsymbol{Y_t} = \Gamma_1 \Delta \boldsymbol{Y_{t-1}} + \Gamma_2 \Delta \boldsymbol{Y_{t-2}} + \ldots + \Gamma_{p-1} \Delta \boldsymbol{Y_{t-p-1}} + \prod \boldsymbol{Y_{t-1}} + \boldsymbol{\varepsilon_t} \tag{2}$$

In this equation, $\prod = \boldsymbol{\alpha\beta}'$ refers the long run parameter. The equation can be restated as follows:

$$\Delta \boldsymbol{Y_t} = \Gamma_1 \Delta \boldsymbol{Y_{t-1}} + \Gamma_2 \Delta \boldsymbol{Y_{t-2}} + \ldots + \Gamma_{p-1} \Delta \boldsymbol{Y_{t-p-1}} + \boldsymbol{\alpha}(\boldsymbol{\beta}' \boldsymbol{Y_{t-1}}) + \boldsymbol{\varepsilon_t} \tag{3}$$

In Equation (3), the expression $\boldsymbol{\alpha}(\boldsymbol{\beta}' \boldsymbol{Y_{t-1}})$ represents the error correction term (ECT). This term contains (m-1) number of vectors. The rank of matrix $\prod$ is denoted by r. If $\boldsymbol{r} \leq (\boldsymbol{m} - 1)$, there is a cointegration relationship between the series (Mert & Çağlar, 2019). p=l-1 should be used as lag length in the cointegration model, such that, 1 minus the lag length determined in the VAR model (Ghali & El-Sakka, 2004). The vector error correction model accepted for analysis in this scenario will be VECM (1). Given the cointegration relationship between the variables in the model with the lnemp data as the endogenous variable, we can make the following economic assessment: even if the equilibrium deviates in the short run from the long-term equilibrium due to shocks, employment will eventually return to the long-term equilibrium level. Diagnostic tests were run on the generated VEC model to determine its reliability. Depending on the number of cointegration vectors detected, a weak externality test was applied to each variable to determine which variables could be used as external variables and whether the model was set up correctly. Restrictions were added to the VEC model and it was structured as a constrained model.

The restrictions were set such that the $\boldsymbol{H}_0 : \boldsymbol{A}_{11} = 0$ hypothesis indicates that the lnemp variable is weakly exogenous, the $\boldsymbol{H}_0 : \boldsymbol{A}_{21} = 0$ hypothesis indicates that the lnexp variable is weakly exogenous, and the $\boldsymbol{H}_0 : \boldsymbol{A}_{31} = 0$ hypothesis indicates that the lngdp variable is weakly exogenous (Alguacil & Orts, 2002).

To assess the causal relationship between the variables, the Granger causality test is applied. The Granger causality test displays the direction of causation between variables over the long and short term. If the series are not cointegrated, the VAR-based Granger causality test can be used; otherwise, the causal relationship should be verified using the VEC-based Granger causality test, as the VAR model may produce biased findings in the occurrence of cointegration. While the ECT coefficient is statistically significant and negative, indicating a long-term causal relationship, F-statistics can be used to test for short-term causal relationships (Riti et al., 2017; Zhang et al., 2019). Instead of expressing real causal relationships, the Granger causality test presents a statistical estimate of causal relationships. It cannot forecast how a variable would respond to an innovation or shock in another variable. These relationships can be explained using impulse response functions and variance decomposition analysis (Zhang et al., 2019).

Vector Error Correction models (VECM) can only infer Granger causality for the dependent variable in a given sample, and therefore offer no insights into the dynamic nature of the system. Impulse Response Functions (IRF) reveal the effects of shocks on a variable

(Trošt & Bojnec, 2015). The IRF is used to analyze the periodic response in the dependent variable when a standard deviation shock is imposed on another variable's residual. The IRF not only reveals the lag periods and lag ranges of a policy's impacts, but also their size and direction (Zhu et al., 2019). The variance decomposition analysis examines how the relative total change is distributed among the series over the periods. In addition, it may be used to determine the relative contributions of various shocks to changes in endogenous variables (Zhang et al., 2019). The variance decomposition analysis is used to estimate how much of the variability of a single variable at time t is due to innovation or shock in that variable or any other variable (Alguacil & Orts, 2002). Consequently, variance decomposition reveals the amount to which a variable contributes to the explanation of another variable, whereas the impulse response function provides information about the level of response of a variable in the presence of a shock on both another variable and itself (Riti et al., 2017).

4. EMPIRICAL RESULTS

4.1. Unit Root Tests

In order to identify the stationarity levels of the series, both level and first differences were investigated with unit root tests, and the findings are presented in Table 3.

Table 3. Unit Root Test Results

	ADF		**PP**	
	Level	1st diff.	Level	1st diff.
VARIABLE	t-Stat.	t-Stat.	Adj t-Stat.	Adj t-Stat.
lnemp	-0.498772	-3.173619	-0.325227	-3.260492
	(-2.971853)	(-2.971853)	(-2.967767)	(-2.971853)
lnexp	-1.586415	-4.80537	-1.622802	-4.807276
	(-2.967767)	(-2.971853)	(-2.967767)	(-2.971853)
lngdp	-2.245293	-3.547208	-1.635875	-3.547208
	(-2.971853)	(-2.971853)	(-2.967767)	(-2.971853)
	KPSS		**Ng-Perron**	
	Level	1st diff.	Level	1st diff.
VARIABLE	LM-Stat.	LM-Stat.	Mz_{α} test Stat.	Mz_{α} test Stat.
lnemp	0.565462	0.20315	-0.21664	-11.7903
	(-0.46300)	(-0.46300)	(-8.10000)	(-8.10000)
lnexp	0.501055	0.098858	-2.42533	-13.7236
	(-0.46300)	(-0.46300)	(-8.10000)	(-8.10000)
lngdp	0.696702	0.249616	1.64738	-8.22765
	(-0.46300)	(-0.46300)	(-8.10000)	(-8.10000)

Critical values at 5% significance level for each calculated test statistics are given in parentheses. Only constant is used as exogenous variable. For ADF test, appropriate lag length is selected by choosing Akaike Information Criterion (AIC) with 7 periods of maximum lags. For unit root tests other than ADF, appropriate Newey-West bandwidth with Bartlett kernel estimation method is selected. The null hypothesis of ADF, PP and Ng-Peron is the series has unit root. The null hypothesis of KPSS tests uses stationarity.

As demonstrated in Table 3, all unit root tests revealed that variables at level are nonstationary at a significance level of 5%, but became stationary at the first differences.

4.2. VAR, Johansen Cointegration and VEC Analysis

To successfully utilize VAR analysis and cointegration analysis, it is essential to identify the optimum lag length. The results of the lag order selection criterion are presented in Table 4.

Table 4. Results of Lag Order Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	115.0387	NA	4.99e-08	-8.299165	-8.155183	-8.256352
1	232.1281	199.4856	1.67e-11	-16.30578	-15.72986	-16.13453
2	248.5583	24.34104	9.95e-12	-16.85617	-15.84830*	-16.55647
3	262.1809	17.15442*	7.61e-12*	-17.19858*	-15.75877	-16.77045*

Except for the SC criterion, according to Table 4, all selection criteria chose a lag length of three. The OLS estimator is employed to estimate the chosen VAR (3) model. In order for the OLS estimator to be consistent, the model must thus confirm the required assumptions.

According to the tests conducted, all characteristic roots are within the unit circle, and the stability condition is provided. In addition, the evaluation of Table 5 reveals that the VAR (3) model meets the OLS assumptions, there are no autocorrelation or heteroscedasticity problems in the model, and the residuals are normally distributed.

Table 5. Diagnostic Tests of VAR Model

Diagnostic Test	Test Statistics Value	P Value
Serial Correlation	**Lag 1** 1.553956	0.1757
	Lag 2 1.423028	0.2014
	Lag 3 1.174330	0.3669
Heteroscedasticity	104.0114	0.5907
Normality	1.699283	0.9452

For serial correlation, Portmanteau Serial Correlation test that has the null hypothesis no serial correlation at lag h was used. For heteroscedasticity, White Heteroscedasticity tests (No cross terms) that has the null hypothesis no heteroscedasticity was used. For normality, Multivariate Normality test with Cholesky of covariance was used with the null hypothesis residuals are multivariate normal.

Table 6 displays the results of the Johansen Cointegration test, which examines the presence of a long-term relationship between the variables.

Table 6. Johansen Cointegration Test Results

Unrestricted Cointegration Rank Test (Trace Statistics)				
Number of cointegrating relations under the null hypothesis	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**P-value***
None	0.63219	36.46575	29.79707	0.0074
At most 1	0.205552	9.460643	15.49471	0.3245
At most 2	0.113333	3.24773	3.841466	0.0715

Unrestricted Cointegration Rank Test (Maximum Eigenvalue Statistics)				
Number of cointegrating relations under the null hypothesis	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**P-value***
None	0.63219	27.00510	21.13162	0.0066
At most 1	0.205552	6.212913	14.26460	0.5860
At most 2	0.113333	3.247730	3.841466	0.0715

*p value denotes MacKinnon-Haug-Michelis (1999) p-values

Under the findings of the Johansen cointegration test, with both Trace statistics and Maximum Eigenvalue statistics, one cointegration is identified between variables. VECM can be utilized since variables are cointegrated.

This methodology allowed the analysis of both long-term and short-term dynamic connections. The lnemp variable was selected as the dependent variable to be evaluated using the determined VEC (2) model, and the obtained long-term relationship is represented by equation (4):

$$\ln \boldsymbol{emp} = \underset{(3.4798)}{6.0990} - \underset{(3.6378)}{0.0844} \ln \exp - \underset{(3.4798)}{0.0572} \ln \boldsymbol{gdp} \tag{4}$$

According to the long-term equation, export and economic growth have a negative long-term impact on employment, and these impacts are statistically significant, as evidenced by the t statistics in parentheses.

Equation (5) illustrates the model for short-term error correction:

$$\begin{aligned}\Delta \ln \boldsymbol{emp}_t &= -\underset{(-0.455)}{0.065}\Delta \ln \boldsymbol{emp}_{t-1} + \underset{(2.094)}{0.283}\Delta \ln \boldsymbol{emp}_{t-2} + \underset{(1.701)}{0.016}\Delta \ln \exp_{t-1} + \underset{(1.320)}{0.013}\Delta \ln \exp_{t-2} \\ &+ \underset{(2.550)}{0.129}\Delta \ln \boldsymbol{gdp}_{t-1} + \underset{(2.638)}{0.128}\Delta \ln \boldsymbol{gdp}_{t-2} - \underset{(-5.525)}{0.256}\boldsymbol{VECT}_t - \underset{(-5.166)}{0.007}\end{aligned} \tag{5}$$

A significant and accountable model must have a negative and statistically significant error correction coefficient (Mert & Çağlar, 2019). The error correction coefficient, as stated in Equation (5), satisfies these two requirements.

Table 7. Diagnostic Tests of VEC Model

Diagnostic Test	Test Statistics Value		P Value
Serial Correlation	**Lag 1**	1.553804	0.1690
	Lag 2	0.710432	0.6954
	Lag 3	0.535176	0.8386
Heteroscedasticity	85.00613		0.4488
Normality	1.595280		0.9529

For serial correlation, Portmanteau Serial Correlation test that has the null hypothesis no serial correlation at lag h was used. For heteroscedasticity, White Heteroscedasticity tests (No cross terms) that has the null hypothesis no heteroscedasticity was used. For normality, Multivariate Normality test with Cholesky of covariance was used with the null hypothesis residuals are multivariate normal.

The VEC (2) model has been determined to be free of autocorrelation and heteroscedasticity and to have normally distributed residuals, which can be seen in Table 7.

Table 8. Weak Exogeneity Test for Variables

Cointegration Restriction	Chi- Square Value	P Value
A(1,1)=0	20.24242	0.000007
A(2,1)=0	0.555593	0.456041
A(3,1)=0	2.942881	0.086257

The null hypothesis of the restriction test is that the variable is weakly exogenous.

When the results of the test for weak externality were analyzed in Table 8, it was discovered that the hypothesis that the lnemp variable was weakly exogenous was rejected, however the hypotheses for the lnexp and lngdp variables were not rejected. This result revealed that the endogenous variable lnemp was properly incorporated into the model.

Table 9. VECM Granger Causality Analysis Results

Dependent Variable	Short Run Causality			Long Run Causality
	$\Delta \ln \boldsymbol{emp}_t$	$\Delta \ln \boldsymbol{exp}_t$	$\Delta \ln \boldsymbol{gdp}_t$	$\boldsymbol{ECT}_{t-1}$
$\Delta \ln \boldsymbol{emp}_t$	-	2.38992	5.88626**	-0.256215***
		(0.1140)	(0.0086)	(0.0000)
$\Delta \ln \boldsymbol{exp}_t$	1.59402	-	0.75033	-0.069182
	(0.2247)		(0.4834)	(0.4987)

$\Delta \ln \boldsymbol{gdp}_t$	2.09702 (0.1457)	2.73986 (0.0856)	-	-0.018626 (0.1277)

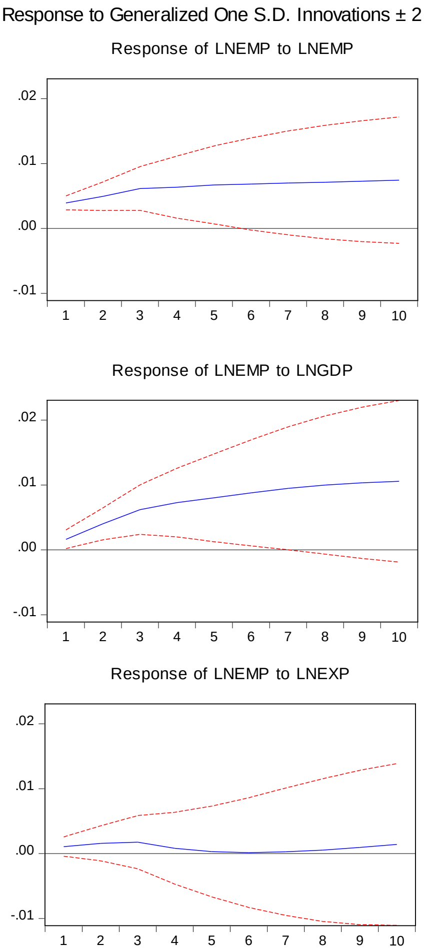
p values are given in the parentheses.

As seen in Table 9, there is only unidirectional Granger causality going from GDP to employment in the short term. The ECT coefficient of the model is negative and statistically significant where $\Delta \ln \boldsymbol{emp}_t$ is utilized as an endogenous variable. This result demonstrates that in the long run, exports and GDP are the driving factors of employment. Additionally, the speed of adjustment toward long-run equilibrium is founded as 25.62%.

As previously stated, the main objective of the study is to determine the effects of exports and GDP on employment. Since employment is assumed to be an endogenous variable in the model, IRF analysis will be used to determine how the employment variable will respond to a shock applied to itself and other variables. Figure 2 illustrates the created IRF graphs.

The graphs show the effects of a standard deviation shock on employment. In all cases, it is seen that the effect of shock on employment is positive. A shock in employment causes a significant increase in itself until the third period and then it stabilizes. After the sixth period, the response becomes insignificant. A shock in GDP causes a significant increase response on employment until the third period, after which the response stabilizes. After the seventh period, the response is not significant. The effect of a shock in export on employment is not statistically significant.

Figure 2. Impulse Response Function



Since our attention is focused on the response of employment to shocks, particularly the shocks on exports and economic growth, only the forecast error variance of the employment is decomposed in response to a one standard deviation shock, innovation, exports, or GDP.

Table 10. Variance Decomposition of lnemp

Period	S.E.	$\mathbf{lnemp}_t$	$\mathbf{\ln exp}_t$	$\ln \boldsymbol{gdp}_t$
1	0.002560	100.0000	0.000000	0.000000
2	0.003384	86.73202	0.373577	12.89441
3	0.004851	54.89151	0.696220	44.41227
4	0.006592	29.86996	14.75363	55.37642
5	0.008501	17.98542	31.38215	50.63243
6	0.010474	12.74808	44.74493	42.50699
7	0.012335	10.27429	53.94864	35.77707
8	0.014114	9.310771	60.67425	30.01498
9	0.015656	8.726412	65.50544	25.76815
10	0.016979	8.430170	68.91508	22.65475

Cholesky Ordering: $lnemp_t$, $lnexp_t$, $lngdp_t$

The variance decomposition results seen in Table 10 show that employment according to the first variance is fully explained by its own shock, which is 100%. In the short run, the contribution rate of employment to itself declines gradually, but in the long run it declines dramatically, reaching 8.43 percent in the tenth period. In the short run, up to the third period, the contribution of exports to employment slightly increases; however, following the third period, it climbs dramatically, reaching 68.91% by the tenth period. The contribution rate of the GDP to employment gradually increases until the fourth period, when it reaches its maximum of 55.37%. After that period, it drops gradually, and it reaches 22.65% in the tenth period.

5. CONCLUSION

After the liberalization of foreign trade, it has been started to be discussed based on traditional trade theories that the increase in exports of countries has positive effects on employment. Many of these discussions are predicated on the theory that a rise in exports stimulates economic growth, which in turn increases employment. In contrast to earlier research, however, current studies have begun to uncover negative effects. As export-oriented industries that create employment in the short term increase their demand for skilled labor in the long-term owing to production restructuring and technological progress, the employment-creating effect of export has been more questionable as the demand for unskilled labor decreases. Basic theoretical expectations contradict this negative relationship, because according to these expectations, as a result of the trade liberalization, the efficiency of resource usage increased and production specialization accelerated, leading to an increase in the employment rate and GDPs of countries.

However, international competition and a more technologically dependent production type at the production stage have altered the type of labor demanded in all industries. While the expansion in exports creates employment for unskilled labor in many developing countries, most sectors in countries that have completed their industrialization and have significantly grown the share of the services sector in employment, have increased the demand for skilled labor. On the other hand, the majority of items formerly produced with labor-intensive production methods have benefited from the production forms provided by technology, resulting in a decline in labor demand and employment.

The empirical analysis of this book chapter examines the causal relationship between employment, export, and GDP. The primary objective of the analysis is to assess the impacts of other variables on employment.

Granger causality analysis indicates the existence of causality running from exports and GDP to employment in the long run. In addition, it was discovered that both export and GDP have a negative and significant effect on employment separately in the long term. In the short run, only the existence of unidirectional Granger causality between GDP and employment was found to be statistically significant. In the short run, only the existence of unidirectional Granger causality between GDP and employment was found to be statistically significant. The GDP has a negative long-run impact on employment but a positive short-run impact. According to the IRF, GDP shocks have a significant and positive effect on employment that last for six periods. Export shocks appeared to have no impact on employment. The results of variance decomposition reveal that while GDP contributes significantly to employment changes in the short run, on the other hand in the long run exports contribute significantly more. The findings of the study are not consistent with traditional international trade theories, but they are consistent with recent findings.

On the basis of this conclusion, it may be inferred that it is essential to adhere to the market's changing expectations and to develop an environment that favors compliance. Policymakers and nongovernmental organizations play an essential role in connecting education and training institutions to business and meeting labor supply and labor demand through active engagement. In a period of accelerating change in the business sector, it is crucial for both employees and employers to improve the processes required to provide the necessary skills and qualifications.

Future studies can contribute to the literature by separating employment according to skilled and unskilled workforce employment, and by specifying the gender differences. Future study should investigate the connection between export and home office labor, new types of employment, as well as the implications of the worldwide Covid-19 pandemic. This phenomena in association with global shocks might be beneficial for advancing understanding and generalizing study findings. Also, recent economic debates tend to question the hypothesis that exports reveal its indirect impacts on employment through the services sector. What is the impact of international commerce, exports, and imports on employment in the services industry? is the new research topic that has emerged from the conclusion of this study.

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