

A Diagnostic Test for the ‘Dutch Disease’ in the U.S.A using the ARDL Bounds Testing Technique

Kwame Asiam Addey^{1,*}

¹Center for Agric. Policy and Trade Studies, North Dakota State University, Fargo, ND, USA

*Corresponding author: 524 Richard H Barry Hall, Center for Agric. Policy and Trade Studies, North Dakota State University, Fargo, ND, USA. Tel: 701-660-9606. E-mail: kwame.addey@ndus.edu

Received: December 19, 2018 Accepted: January 12, 2019 Published: March 25, 2019

doi: 10.5296/rae.v11i1.14074 URL: <https://doi.org/10.5296/rae.v11i1.14074>

Funding Agency: Department of Agribusiness and Applied Economics, North Dakota State University.

Abstract

This study examines the impact of the most recent oil boom on North Dakota’s agricultural sector. I employ the autoregressive distributive lag (ARDL) model to examine short and long run relationships among four labor competing sectors. The model produces an optimal lag order of ARDL (6,6,6,5). Results reveal an 80% speed of adjustment coefficient. This implies that about 80% of any disequilibrium caused by a shock to the economy can be corrected within a quarter of a year. The oil sector has a negative and positive impact on the agricultural and construction sectors respectively but no significant impact on the manufacturing sector. The impulse response function (IRF) from an orthogonalized structural vector autoregression (SVAR) matrix system revealed no deviation from the boom period equilibrium agricultural GDP. Structural spending policies are recommended to curb the negative effects of another oil boom on labor competing sectors. The introduction of an agricultural wage transfer tax will also be helpful in the event of another oil boom.

Keywords: ARDL; Dutch-disease; Oil production; North Dakota; Shale-fracking

JEL Classification Codes : E24 ; Q24 ; Q33.

1. Introduction

The objective of this study is to analyze the impact of the recent oil boom (2005-2015) on North Dakota’s agricultural sector. World oil production has been on the ascendency within the past decade, causing a drastic downward trend in oil prices. For the US, North Dakota is one of the major oil producing states. The Labor Market Information Center of Job Service North Dakota (2015) stated that the oil boom of the state increased employment, wages and business growth to pre-recession levels for the state. This enabled the state to have its lowest average unemployment rate since 2008. The American Petroleum Institute projects the creation of 114,240 jobs in North Dakota from hydraulic fracturing and horizontal drilling by the year 2020. The critical questions to be asked are; where will the projected labor requirements come from? And which sectors of the economy are likely to compete for the scarce labor?

From macroeconomic theory, it is likely that labor demand for the oil sector would have a resource movement effect on agriculture, manufacturing and construction. Graphical observations of the nominal gross domestic products of the three subsectors reveal fluctuating trends over the boom period (Figures 1 and 2). Particularly, the agricultural sector shows more of a downward trend in the last few quarters. This performance projects the possibility of the economic Dutch Disease (DD). Gressley (2015) evaluated the effects of North Dakota state’s oil discovery on the state economy. She identified high transportation costs, shortage of rail car capacity, local supply and demand conditions and the lack of local storage capacity as being responsible for decline in agricultural productivity. In their study of the impact of abundant natural resources on economic growth, Sachs and Warner (1995, 2001) iterated that the abundance of a natural resource has a negative impact on economic growth. Their study showed that a 10% increase in the natural resources to the GDP ratio led to a reduction in the manufactured export growth.

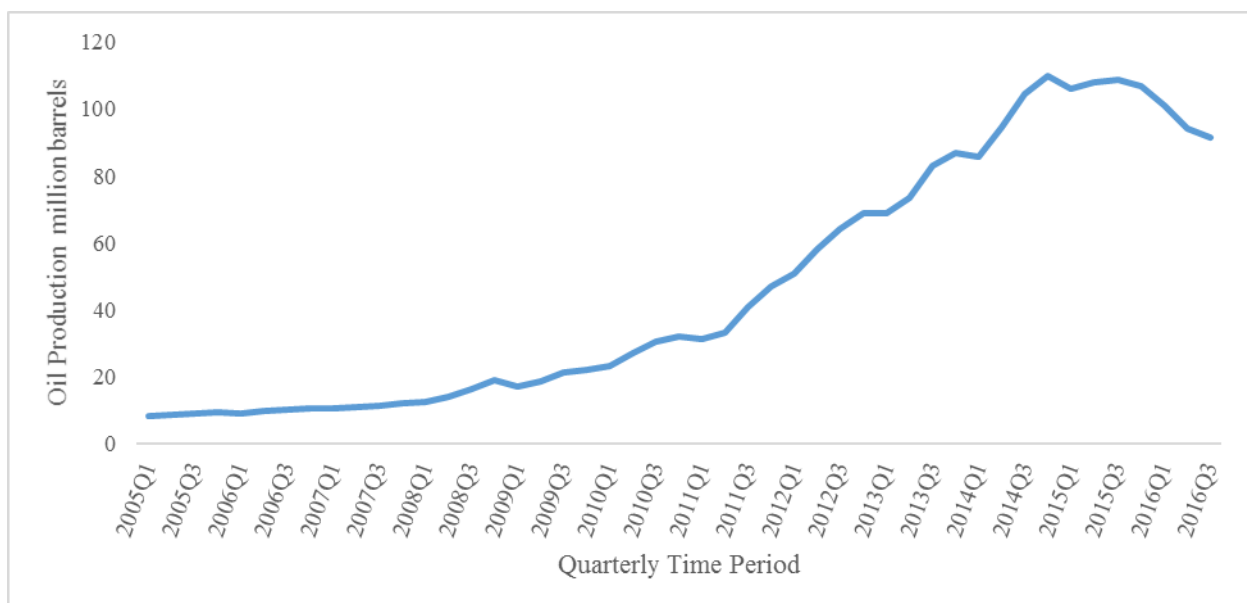


Figure 1. North Dakota State Oil Production **Source:** US Energy Information Agency

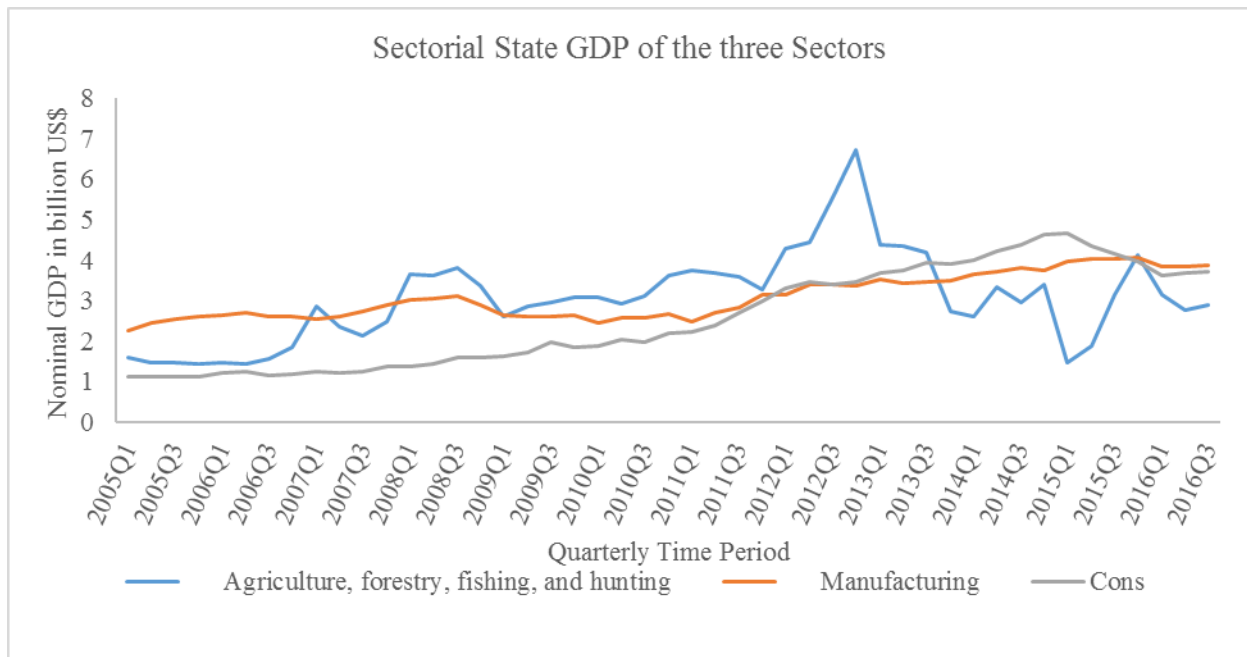


Figure 2. State Sectoral GDP of the Three Labor Interactive Sectors

Source: Bureau of Economic Analysis (U.S. Department of Commerce)

Miljkovic and Ripplinger (2016) studied the labor impacts of oil development in North Dakota using a variant of the Corden-Neary resource development model. They found that; employment and wages had increased in the oil sector while agricultural and rest of economy wages fell relative to the oil and gas sector. They concluded that the increase in the oil and gas sector employment and wages led to a decrease agriculture and rest of the economy employment. Their analysis included data from both the boom and non-boom periods. The current study focuses on only the boom period. Secondly, their study employed hourly wage rate while I employ the gross domestic production which constitutes labor productivity.

This paper is organized into five sections. Section 2 provides a summary of empirical studies on the impact of resource booms on an economy. The third section presents the data sources, theoretical and econometric estimation methods employed in the analysis. The penultimate section has the results and discussions while section 5 summarizes the conclusions and policy recommendations.

2. Literature Review

The economic Dutch disease is defined as the apparent causal relationship between a booming sector and a declining sector within an economy. In most cases the booming sector is a tradable sector such as oil or mineral sector and in some rare cases exportable agricultural cash crop. The declining sector may include the non-tradable agricultural sector, manufacturing or construction sector. In modern economic theory, it is used to describe the negative effects on certain sectors within an economy due to the influx of foreign direct

investments. This phenomenon was named as the Dutch disease in 1977, after the discovery of natural gas in Groningen in 1959 had negative impacts on the Dutch manufacturing sector.

Sectors within every economy are connected by certain inputs or resources. The demand for labor by subsectors within an economy is no exemption from this case. Labor is generally classified as skilled and unskilled. The intersectoral movement of skilled labor is often very restrictive due to time, financial and other material investments required for training. However, less restriction is placed on unskilled labor movements between sectors in an economy because training does not require much time and financial investments. This presents a dimension of the effects of the Dutch disease known as resource movement effects. Studies have shown that this issue is unfavourable for the agricultural sector due to low wages in this sector. This is attributed to the fact that the impact of a boom in a tradable resource leads to an increased demand for labor which is drawn from non-tradable sectors within the same economy leading to the marginalization of these sectors.

Kareem (2010) investigates the structural manifestation and implications of the Dutch disease due to permanent oil price shocks on oil exporting countries. Four main conclusions were drawn. 1) Permanent increase in oil prices negatively affect production in the manufacturing sector. 2) Oil windfall shocks were found to have stronger impacts on manufacturing sectors in countries with more open capital markets to foreign investment 3) Relative factor price of labor to capital and capital intensity in manufacturing sectors appreciated as windfall shocks increased. 4) The manufacturing sectors with higher capital intensity were less affected by windfall shocks than their counterparts. Michaels (2010) revealed that counties that are rich in oil resources specialized in oil production, but this did not lead to a reduction in growth of the other sectors. His study included a total of 775 oil abundant counties in southern United States using a time series from 1940 to 1990. The states from which these counties were drawn are Texas, Oklahoma and Louisiana. The estimation was done using an ordinary least squares regression.

Weber (2012) studied the effects of natural gas boom on employment and income in three U.S states. His study employed county level data totaling 338 counties over a time from 1998 to 2008. Using the OLS and instrumental variable regression, he found that a boom county exhibited higher growth in total employment, wage and salary income. However, his study does not exactly address the effects on sectors that are vulnerable. Raveh (2013) constructed a simple tax competition model as a methodological framework of analysis. The results showed that if factor mobility costs are sufficiently low, a resource-boom triggers an Alberta Effect that mitigates, and possibly reverses Dutch disease symptoms. The data employed involved a panel data of 238 provinces over different time periods. Three conclusions drawn from his paper are 1) Resource-abundant states had a more competitive business environment and attracted more physical capital per capita than resource-poor states did. 2) The business environment channel accounted for approximately 60% of resource-induced inflows of physical capital. 3) The manufacturing sectors of resource-abundant states were found to grow relatively faster than the resource-poor states' manufacturing sector. This enhanced the reversal of the effects of the Dutch disease in the former and passed them to the latter.

Onel and Goodwin (2014) found that large elasticities between economic incentives and out-farm migration are observed after a high threshold of wage differential between farm and off-farm sectors is surpassed. Their study used annual U.S. employment data from 1948 to 2009. Weinstein (2014) studied the impacts of innovations in hydraulic fracturing at the county level across the United States. County level data of 3060 counties of the 48 states from 2001 to 2011 was used. With the objective of comparing boom counties to non-boom counties, the standard difference-in-difference method was used. Boom counties were found to experience increase in both employment and earnings. However, the impact on earnings was approximately double that of employment. This study concludes that shale development had modest impact on employment despite having significant impacts on earnings. The employment multiplier from oil and gas development is estimated to be 1.3.

Munasib and Rickman (2015) studied the economic impact of shale gas and tight oil boom on Arkansas, Pennsylvania and North Dakota using the synthetic control method (SCM). The SCM method which is a relatively rare method in analysis in the study of the Dutch disease in was used to establish a baseline projection for the local economies in the absence of increased shale-based energy extraction. This allowed for the estimation of its net regional economic effects. For North Dakota, the oil and gas counties were revealed to have a higher share of college graduates and were more remote. Also, they were found to have negative natural population growth and most notably had become less farm dependent. The synthetic growth of the oil and gas sector were found to have been highly driven by the South Dakota counties (which made up 65% of the total growth). They significantly noticed that the oil and gas counties in North Dakota were relatively more isolated in comparison to Arkansas. It was revealed using macroeconomic indicators that the North Dakota economy was far less attractive prior to the boom. Total employment and wages had risen by 17% and 19% respectively. From a spatial perspective, they found that oil and gas counties had become less farm-dependent, more amenity attractive and less remote.

3. Data and Method of Analysis

3.1 Data Sources

Secondary quarterly data from 2005 to the third quarter of 2016 was used for this study. North Dakota oil production data was obtained from the U.S. Energy Information Administration (EIA). This variable is measured in thousands of barrels. Agricultural, manufacturing and construction GDP were obtained from the Bureau of Economic Analysis (BEA). The GDPs of the three sectors were logged.

3.2 Theoretical Economic Framework

The theoretical model of the impact of a resource development is based on Corden and Neary (1982). It separates the effects into resource movement effect and spending effect. Various literature either apply both concepts or one of them for their analysis depending on the study area and data available.

The stationarity of the variables was tested using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Though both primarily perform the same purpose, the advantage of the PP test is to identify the presence of unknown forms of autocorrelation with a structural break in the model. When variables are found to be non-stationary, the conventional econometric solution has been to difference the series successively until stationarity is achieved. However, Asteriou and Hall (2007) explained that this resolution mechanism eliminates the possibility of a unique long-run solution due to the process of differencing the error process in the regression. This is disadvantageous since the auxiliary purpose of the unit root test is to identify the existence of co-integration among the variables. In time series literature, the relationships for variables that are I (1) at levels can be determined with the use of the Johansen (1995) cointegration test. But because the variables revealed mutually cointegrated levels of stationary between I (1) and I (0), the Pesaran *et al.*, (2001) autoregressive distributed lag (ARDL) bounds testing approach to cointegration analysis was used. In cases of mutually cointegrated stationarity levels, OLS estimates produce significant t-statistic values that have divergent distributions. That notwithstanding, spurious results which have R-squared values being higher than the Durbin-Watson statistics will be produced. The other preconditions for estimating the ARDL model include; variables must not have beyond I (2) for the unit root test and the absence of I (2) in the structural breaks for the variables. Results of the stationarity test can be found in Table 1.

Table 1. Results of Unit Root Test

Variable	ADF test		PP test	KPSS test	
	Log form	1st diff	Log form	Log form	1 st diff
Agricultural GDP	0.329	-6.102***	-2.249	0.232	0.0483*
Oil Production	2.592**	2.592**	-0.433	0.153	0.24*
Manuf. GDP	1.447	-3.459***	-2.042	0.177	0.0779*
Construction GDP	2.417**	-3.213***	-0.754	0.154	0.188

3.3 The ARDL Model

The long-run relationship among the variables was identified using the ARDL (Pesaran and Shin, 1999). This method yields consistent and asymptotically normal short-run parameters. It also leads to correspondent super-consistent long-run parameters of the regressors at I(1) and asymptotically normal estimates irrespective of the order of integration. The ARDL (p,q ,.....,q) can be represented as;

$$\ln y_t = a_0 + a_1 t + \sum_{i=1}^p \phi_i \ln y_{t-i} + \sum_{i=0}^q \beta_i' \ln x_{t-i} + \mu_t \quad (1)$$

where $t = \max(p, q), \dots, T$, for simplicity it is assumed that the lag order q is the same for all variables in the $K \times 1$ vector x_t . The variables in $((y_t, x_t)'$ can be purely I (0), purely I (1), or cointegrated. The optimal lag orders p and q can be obtained by minimizing the Akaike

Information Criterion (AIC). According to Liew (2004), the appropriate selection criteria for observations less than 60 as in the case of this study are the AIC and the Final Prediction Error (FPE). Reparameterization in the conditional unrestricted error correction form yields;

$$\ln y_t = a_0 + a_1 t - \delta (\ln y_{t-1} - \theta \ln x_{t-1}) + \sum_{i=1}^{p-1} \varphi_{y_i} \Delta \ln y_{t-i} + \omega' \Delta \ln x_t + \sum_{i=1}^{p-1} \varphi_{x_i} \Delta \ln x_{t-i} + \mu_i \quad (2)$$

where the speed-of-adjustment coefficient $\delta = 1 - \sum_{i=1}^{q-1} \phi_i$ and the long-run coefficients $\theta = \frac{\sum_{j=0}^q \beta_j}{\delta}$. The long-run association is then tested using an F-test.

3.4 Structural VAR model for Impulse Response Functions

The recursive vector autoregression (VAR) is used to forecast the impact of an external shock to the economy. It incorporates the Cholesky decomposition and the structural VAR. The recursive VAR is order-dependent but the strength of the SVAR lies in its in-built orthogonalization of matrix P. The contemporaneous short run restrictions are rather imposed on the covariances between the shocks. Bernanke (1986) perceived these structural innovations as primitive exogenous forces which are mostly not directly observed by the researcher but still buffers the system and causes oscillations and hence treating them as uncorrelated is justifiable. Therefore, restrictions can be placed on the long-run accumulated effects of the shocks.

Sims (1980) explained that the method of identifying restrictions in the SVAR model helps to avoid problems in dynamic simultaneous equation models which consistently end up with incredible identifying restrictions. This further eliminates the difficulty of identifying truly endogenous variables which is a setback concomitant with the use of traditional VAR model. Another advantage of SVAR model is the ability to accommodate dynamic covariance just as in multivariate GARCH and stochastic volatility models (Chib *et al.*, 2009). Finally, Gottschalk (2001) stated that dynamic simultaneous equations models are better suited for policy simulations while the SVAR models yield optimal outcomes when used for the analysis of monetary transmission mechanism. Since the impact of oil production on the agricultural sector is based on sectoral wage differentials and global oil price shocks, it makes these models more inclined to a monetary transmission mechanism and hence the justification for the use of the SVAR model for this study.

The ARDL model from a matrix representation can be simplified as $BZ_t + \tau_0 + \tau_0 Z_{t-1} + \varepsilon_t$. The standard form of the VAR can be obtained by multiplying the ARDL matrix connotation through by the inverse of matrix B to give $Aq_t = c + A_1 Z_{t-1} + \dots + A_p Z_{t-p} + \varepsilon_t$. The error terms are the composites of the structural impulses from the SVAR. The test for identification of the structural innovation on the dependent variables would require the recovery of parameters from the estimated system. For exact identification, Sims (1980) stated that if all the elements above the diagonal of the matrix are restricted, the system can

be expressed as being exactly identified. This is known as the Cholesky decomposition. In this study, the Cholesky decomposition is defined into matrix A and B where the matrix A imposes the recursive structure and the matrix B orthogonalizes the effects of the shocks.

4. Results and Discussions

The results reveal an optimal lag order of ARDL (6,6,6,5). Agricultural GDP is used as the dependent variable, obtaining $\ln Ag_t = f(\ln Oil_t, \ln Manu_t, \ln Con_t)$. The speed of adjustment towards long run equilibrium (error correction term) is significant at 1% with a negative coefficient of 0.80. This implies that about 80% of any disequilibrium caused by a shock to the economy can be corrected within a quarter of a year. The regression model reveals that oil production and construction GDP have negative and positive long-run effects on agricultural GDP respectively.

The negative impact of oil production can be attributed to the discovery of new oil rigs and sites (Bangsund and Hodur, 2013). These new oil sites are likely to compete with the agricultural sector for lands. Hence, the loss of these agricultural lands to the oil sector can accrue into a systematic decline in the agricultural GDP growth of the state. McGranahan *et al.*, (2017) confirmed that agricultural landowners had challenges with land take-overs from oil companies in the Bakken Shale area. In addition, transfer of labor from the agricultural sector to the oil production sector can also lead to this negative relationship. Construction GDP includes agricultural related infrastructure which increases productivity in the agricultural sector. Hence, increment in construction GDP will have a positive impact on agricultural GDP. The results from the conditional ECM reveals similar estimates and direction. Results of both models of the ARDL (6,6,6,5) can be found in Table 2.

The Pesaran *et al.*, (2001) ARDL bounds test depends on two main approaches to determine the existence of a long run cointegration relationship among the first differenced variables ($Ag_t, Oil_t, Manu_t, Con_t$). These can be done by either comparing the F-test or t-statistic with the lower bound from the bounds test or comparing them with the upper bound. The underlying hypothesis is that there is no relationship among the variables at levels. The decision rule is to fail to reject the null hypothesis if the test statistic is less than the critical lower bound or to reject the null hypothesis if the test statistic is greater than the critical higher bound values. The F-statistic is 4.680 and greater than the lower bound at both the 5 (3.77) and 10% (2.72) levels of significance. This value is greater than the upper bounds of the 5 and 10% levels of 3.77 and 4.35 respectively. Hence, the null hypothesis is rejected. It can be inferred that there is a long run relationship among the variables. Details of these results are in Table 3.

Table 2. Error Correction Models of Agricultural GDP for the ARDL Model

Unrestricted ECM of ARDL (6, 6, 6, 5)				Conditional ECM of ARDL (6,6,6,5)		
D.LnAg1	Coefficient	Std. Err.	t-stat	Coefficient	Std. Err.	t-stat
Speed of Adjustment Coefficient (LnAg1)						
L1.	-0.8015	0.4816	-1.66	-0.8015	0.4816	-1.66
Long-run Relationship						
LnOil1	-11.7886***	7.9984	-1.47	-9.4485***	2.7422	-3.45
LnManu1	-4.0479	3.6748	-1.10	-3.2444	1.8465	-1.76
LnCon1	12.7628**	8.8857	1.44	10.2294**	3.5193	2.91
Short-run Relationship (LnAg1)						
LD.	-0.4628	0.4535	-1.02	-0.4628	0.4535	-1.02
L2D.	-0.4069	0.4019	-1.01	-0.4069	0.4019	-1.01
L3D.	-0.5572	0.3207	-1.74	-0.5572	0.3207	-1.74
L4D.	-0.3369	0.2378	-1.42	-0.3369	0.2378	-1.42
L5D.	-0.1664	0.1722	-0.97	-0.1664	0.1722	-0.97
LnOil1						
D1.	8.7535***	2.3789	3.68	8.7535***	2.3789	3.68
LD.	5.1465**	1.9656	2.62	5.1465**	1.9656	2.62
L2D.	4.6495***	1.4773	3.15	4.6495***	1.4773	3.15
L3D.	2.4105*	1.2281	1.96	2.4105*	1.2281	1.96
L4D.	2.1438**	0.8571	2.5	2.1438**	0.8571	2.5
L5D.	2.6277***	0.7506	3.5	2.6278***	0.7506	3.5
LnManu1						
D1.	-0.2221	1.5795	-0.14	-0.2221	1.5795	-0.14
LD.	1.2733	1.5673	0.81	1.2733	1.5673	0.81
L2D.	5.7613***	1.5682	3.67	5.7613***	1.5682	3.67
L3D.	4.1509**	1.4456	2.87	4.1509**	1.4456	2.87
L4D.	2.3612	1.3698	1.72	2.3612	1.3698	1.72
L5D.	1.4722	0.9457	1.56	1.4722	0.9457	1.56
LnCon1						
D1.	-8.2700**	3.1834	-2.6	-8.2700**	3.1834	-2.6
LD.	-7.3272**	2.5498	-2.87	-7.3272**	2.5498	-2.87
L2D.	-8.0496***	2.2396	-3.59	-8.0496***	2.2396	-3.59
L3D.	-5.6874***	1.5545	-3.66	-5.6874***	1.5545	-3.66
L4D.	-1.9048*	1.000	-1.9	-1.9048*	1.000	-1.9
Constant	0.3007	0.083	3.62	0.3007	0.083	3.62
Number of Observations				F (26, 13)		
40				6.58		
R-Squared				Prob>F		
0.9294				0.0005		

*** and ** are 1 and 5% statistical level of significance respectively

Table 3. Bounds Test for the Existence of a Long Run Relationship

Critical Values	F-Statistic =4.680		H_0 =No long run relationship
	Lower Bound I (0)	Upper Bound I (1)	Decision Rule
1%	4.29	5.61	Fail to reject null
5%	3.23	4.35	Reject null hypothesis
10%	2.72	3.77	Reject null hypothesis

Post-estimation diagnostic tests of model residual fitness were conducted. The Shapiro-Wilk normality test was used to validate the normality assumption. The presence of first order autocorrelation was conducted using the Durbin-Watson rho. The null hypothesis of no correlation was maintained. In econometric modelling, the use of time series is under an assumption of constant variance. But the presence of the autoregressive conditional heteroskedastic (ARCH) process causes the temporal conditional variance to be a function of the past errors, leading to an unconditional constant variance. The presence of the ARCH effects in a time series model will lead to unbiased and consistent estimates. However, the standard errors would be inconsistent. This will produce inconsistent hypothesis test statistics and confidence intervals. To identify the absence of the ARCH effects, the Lagrange multiplier test was used

The presence of serial correlation will not affect the consistency of estimates if the independent variables do not contain lagged values of the dependent variables. When it occurs, serial correlation may lead to biased standard errors, inappropriateness of the F-statistics or t-statistics for inferences due to increased possibilities of type I or type II errors. The Breusch-Godfrey LM test for autocorrelation revealed that there is no serial correlation in the model. The Durbin-Watson test for higher order autocorrelation which has the advantage of testing for both positive and negative autocorrelation was conducted. The Breusch-Pagan test for constant variance was also performed. Finally, the variance inflation factor (VIF) was used to test for multicollinearity. The summary of all post-estimation tests is in Table 4.

The Structural VAR was used to identify the impact of a shock on the model through an impulse response function. The target variable for the impulse in this model is agricultural GDP. The identifying restrictions for the SVAR model were imposed prior to the determination of short run relationships. This is the restriction that distinguishes the Structural VAR methodology from the traditional dynamic simultaneous equation method. This assumes that structural innovations are orthogonal and hence a variance-covariance matrix $e(A)$ and $e(B)$ are established, where $e(B)$ is restricted to zero. The model was found to be exactly identified. The diagnostics for the SVAR are further tested for model accuracy. The LM test on 4 lag orders of the SVAR revealed no autocorrelation. The Jarque-Bera test revealed normality for the overall SVAR equation despite the target model not being normal. The test for stability of the model revealed that all the eigen values lied within the unit circle and hence the model satisfied the stability condition. The high probability of the temporal variation of time series data increases the chances of obtaining unstable parameters which may lead to model misspecification and bias estimates. Having established the model

appropriateness, the variance decomposition and impulse response functions were obtained.

Table 4. Summary of Post-Estimation Diagnostic Tests

Diagnostic Test	Null Hypothesis	Test Score	Critical Value (5%)	Decision Rule
Normality	H_0 : residuals are normally distributed	Shapiro-Wilk W (0.824)	Prob>z (0.1000)	Fail to reject the null hypothesis
First order autocorrelation	$H_0: \rho = 0$	d-statistic (1.827)	$d_L(20,40) = 0.430$ $d_U(20,40) = 2.974$	Fail to reject the null hypothesis
ARCH(p) effects	H_0 : no ARCH effect	<i>chi2</i> statistic (0.969)	Prob> chi2 (0.3249)	Fail to reject the null hypothesis
Serial correlation	H_0 : no serial correlation	<i>chi2</i> statistic (0.505)	Prob> chi2 (0.4772)	Fail to reject the null hypothesis
Heteroskedasticity	H_0 : Constant variance	<i>chi2</i> statistic (5.80)	Prob> chi2 (0.160)	Fail to reject the null hypothesis
Omitted variable test	H_0 : no omitted variables	F (3,10) statistic (2.22)	Prob> F (0.1487)	Fail to reject the null hypothesis

To successfully predict the response of the target variable to an exogenous shock, the SVAR model must satisfy the following conditions; no autocorrelation at highest lag order, normality and model stability. Hence these characteristics were tested. The Lagrange-multiplier test was used to test for the absence of autocorrelation at each of the six lag orders. However, the lag orders of importance were the 5th and 6th lag orders because the model was found to be distributed at ARDL (6,6,6,5). The chi probability values were 79.71 and 80.38% respectively and therefore the null hypothesis of no autocorrelation at lag order could not be rejected. All other lag orders were also found to maintain the null hypothesis. The Jacque-Bera test for normality of the SVAR residuals were 15.61%, 85.055%, 66.50% and 71.32% for the agricultural GDP, oil production, manufacturing GDP and construction GDP respectively. These percentages indicated that the null hypothesis of normality could not be rejected.

An observation of the response of agricultural sector to an external change in the oil production sector reveals no deviation from the equilibrium agricultural GDP established during the boom period. The number of periods considered in this IRF model is 20 quarters (5 years). This was used because decline in oil production due price shocks will not immediately affect the agricultural sector significantly for these reasons; land claimed and used for oil fields cannot be immediately returned for agricultural production, and labor drawn from the agricultural sector would not immediately go back into agricultural employment due to the wide wage differential between the two sectors. Such individuals would rather prefer to migrate elsewhere than to go back into the agricultural sector which has relatively lower wages. The result of the impulse response function is found in Figure 4.0.

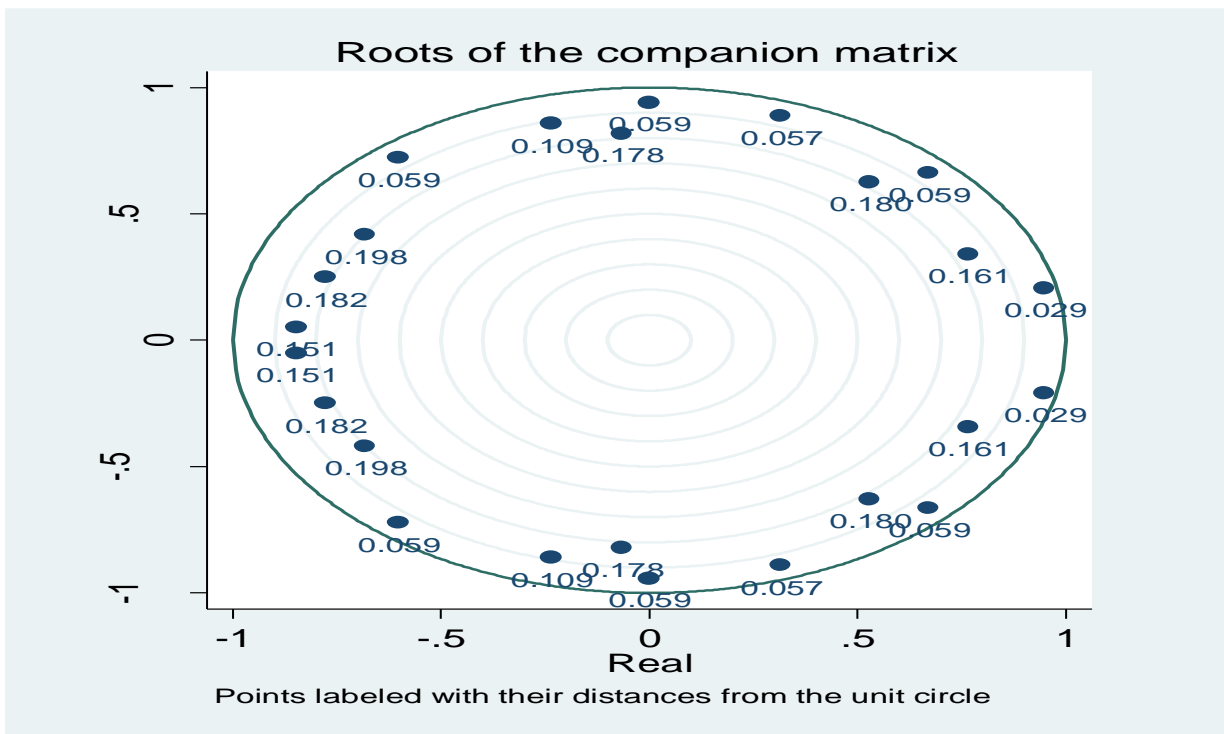


Figure 3. Eigenvalue Stability Condition

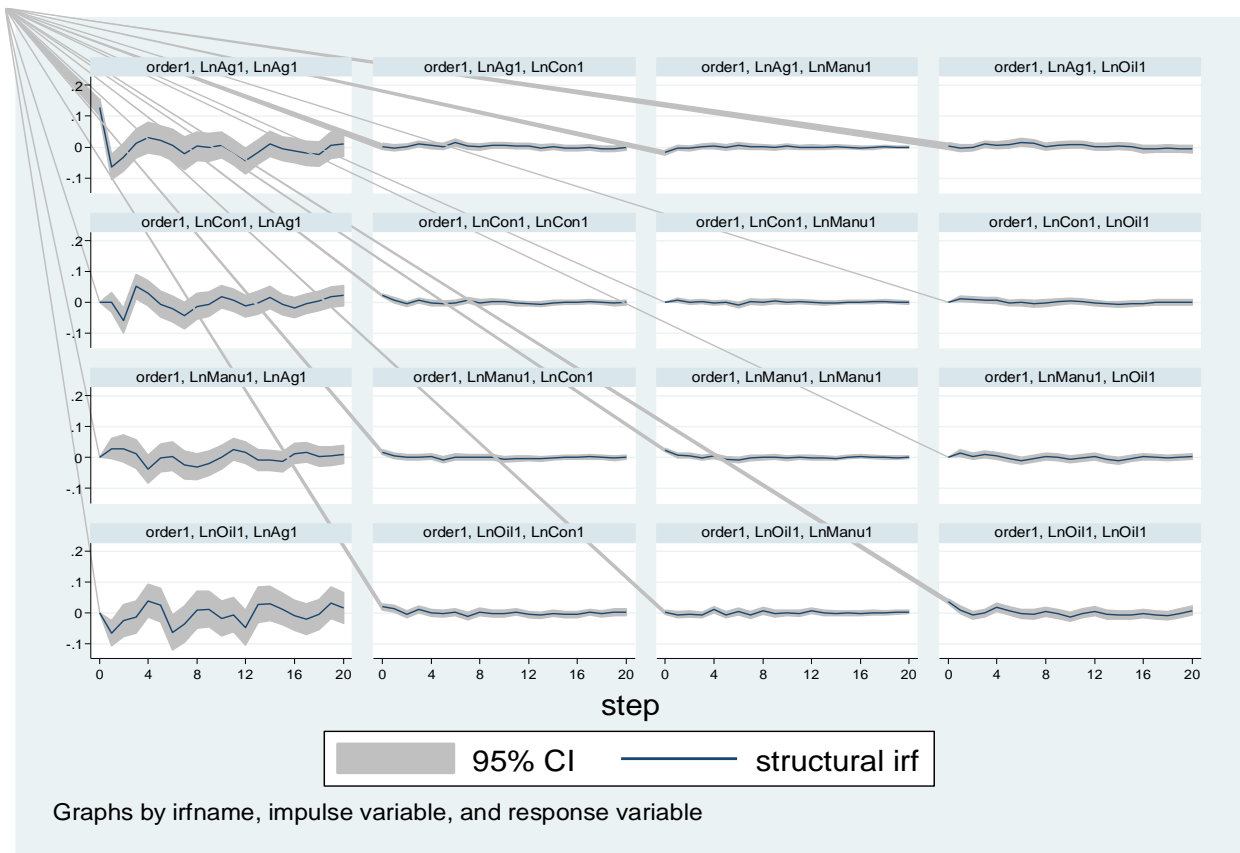


Figure 4. Impulse Response Function

5. Conclusions and Policy Recommendations

North Dakota is among the least dense states (47th as at 2016) in USA. It has great potential for economic expansion considering the recently improved efficiency of production in the oil industry. However, its implications on other sectors may not be favorable if not handled with economic dexterity. There have been several studies to substantiate this premise. Also, the effects of the identification of a new tradable resource or a boom due to improved production efficiency has been widely discussed over the latter half of the last century. This paper examined the effect of the recent oil boom on the state's agricultural sector. The conditional unrestricted error correction model was used to determine long run relationships among four labor competing sectors (oil, agricultural, manufacturing and construction). The structural VAR model was employed to identify short run relationships among these sectors and forecast the response of the agricultural sector to an external structural shock. The speed of adjustment to long run equilibrium was 80%. The oil sector was found to have had a causal effect on the agricultural and the construction sectors but not the manufacturing sector. An impulse shock on the oil sector will cause no further deviation from the current equilibrium GDP of the agricultural sector.

The introduction of an agricultural wage transfer tax in the oil sector is recommended to mitigate the effects of another boom. The Dutch disease can also be curbed in the state through spending and structural policies. For instance, expenditures on private firms must be increased to boost the production efficiency and productivity of local firms. This form of spending will eventually boost productivity of the non-tradable sectors. Finally, infrastructural developments within the transportation industry will also harness the productivity of non-tradable sectors.

References

- American Petroleum Institute (2014). Oil and Natural Gas Stimulate North Dakota Economic and Job Growth. Retrieved from <http://bakkenoilreport.com/oil-natural-gas-stimulate-north-dakota-economic-and-job-growth/>
- Asteriou D., & Hall S.G. (2007). Applied Econometrics: A Modern Approach Using Eviews and Microfit. *Palgrave Macmillan*. Revised Edition.
- Bangsund D. A., & Hodur, N. M. (2013). Petroleum industry's economic contribution to North Dakota in 2011. *Agribusiness and Applied Economics Departmental Report No. 710*.
- Bernanke B. S. (1986). Alternative Explanations of the Money-Income Correlation. *In Carnegie Rochester Conference Series on Public Policy*, 25, 49-100. [https://doi.org/10.1016/0167-2231\(86\)90037-0](https://doi.org/10.1016/0167-2231(86)90037-0)
- Chib S., Omori Y., & Asai M. (2009). Multivariate Stochastic Volatility, in: T.G., &ersen, R.A. Davis, Kreiss J-P., & Mikosch T. (Eds.), *Handbook of Financial Times Series*,

- Springer-Verlag, New York, 365-400. https://doi.org/10.1007/978-3-540-71297-8_16
- Corden W. M., & Neary J. P. (1982). Booming Sector and De-industrialization in a Small Open Economy. *Economic Journal*, 92(368), 825-848. <https://doi.org/10.2307/2232670>
- Gottschalk J. (2001). An introduction into the SVAR Methodology: Identification, Interpretation and Limitations of SVAR models. *Kiel Working Paper No. 1072* Kiel Institute of World Economics
- Gressley J. (2015). The Effects of North Dakota Oil Production on the Minnesota Economy. *An Auber Brief for IHS*.
- Johansen S. (1995). *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford University Press: Oxford. <https://doi.org/10.1093/0198774508.003.0001>
- Kareem I. (2010). The Structural Manifestation of the 'Dutch Disease': The Case of Oil Exporting Countries. *IMF Working Paper*. WP/10/103. <https://doi.org/10.5089/9781455200627.001>
- Labor Market Information Center of Job Service North Dakota (2015). *North Dakota Workforce Review*. Labor Market Information Center of Job Service North Dakota. <https://doi.org/10.5203/lwbin.gnd.2014.1>
- Liew, V. K-S (2004). What lag selection criteria should we employ? *Economic bulletin*, 33(3), 1-9.
- McGranahan D. A., Fernando F. N., & Kirkwood M. L. E. (2017). Reflections on a boom: Perceptions of energy development impacts in the Bakken oil patch inform environmental science & policy priorities. *Science of the Total Environment*. 599-600, 1993-2018. <https://doi.org/10.1016/j.scitotenv.2017.05.122>
- Michaels G. (2010). The long-term Consequences of Resource-Based Specialization. *The Economic Journal*, 121, 31-57.
- Miljkovic D., & Ripplinger D. (2016). Labor market impacts of U.S. tight oil development: The case of the Bakken. *Energy Economics*, 60, 306-312. <https://doi.org/10.1016/j.eneco.2016.10.007>
- Munasib A., & Rickman D. S. (2015). Regional economic impacts of the shale gas and tight oil boom: A synthetic control analysis. *Regional Science and Urban Economics*, 50, 1-17. <https://doi.org/10.1016/j.regsciurbeco.2014.10.006>
- Onel G., & Goodwin B. (2014). Real Options Approach to inter-sectoral migration of U.S. Farm labor. *American Journal of Agricultural Economics*, 96(4), 1198-1219. <https://doi.org/10.1093/ajae/aau004>
- Pesaran H. M., & Shin Y. (1999). Autoregressive distributed lag modelling approach to cointegration analysis. Chapter 11 in *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, Strom S(Ed.). Cambridge University Press: Cambridge. <https://doi.org/10.1017/cbo9781139052221.011>

- Pesaran H. M., Shin Y., & Smith R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16, 289-326.
<https://doi.org/10.1002/jae.616>
- Raveh O. (2013). Dutch Disease, factor mobility, and the Alberta Effect: the case of federations. *Canadian Journal of Economics*, 46(4), 1317-1350.
<https://doi.org/10.1111/caje.12050>
- Sachs J. D., & Warner A. M. (1995). Natural Resource Abundance and Economic Growth. *National Bureau of Economic Research*. Working Paper 5398. Cambridge MA.
[https://doi.org/10.1016/s0014-2921\(01\)00125-8](https://doi.org/10.1016/s0014-2921(01)00125-8)
- Sachs J.D., & Warner. A.M. (2001). Natural Resources and Economic Development The curse of natural resources. *European Economic Review*, 45, 827-838.
- Sims C. (1980). Macroeconomics and Reality. *Econometrica*, 48(1), 1-49.
- Weber J. G. (2012). The effects of a natural gas boom on employment and income in Colorado, Texas, and Wyoming. *Energy Economics*, 34(5), 1580-1588.
<https://doi.org/10.1016/j.eneco.2011.11.013>
- Weinstein A. L. (2014). Local labor market restructuring in the Shale Boom. *Journal of Regional Analysis and Policy*, 44(1), 71-92.

Copyright Disclaimer

Copyright for this article is retained by the author(s), with first publication rights granted to the journal.

This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution license (<http://creativecommons.org/licenses/by/3.0/>).