Does oil price affect New Mexico's unemployment rate in the short term ? An SVAR approach (2010-2019)

Gabriel AMMOUR* and Noa LE ROUX*

*2^{nd} year students in Applied Econometrics, Nantes Université

February 9, 2025

Abstract

This study investigates the short-term impact of oil price fluctuations on the unemployment rate in New Mexico, a state with a significant reliance on the energy sector. Using a Structural Vector Autoregressive (SVAR) model, we analyze the relationship between West Texas Intermediate (WTI) crude oil prices, the New Mexico unemployment rate (NMUR), the industrial production index (INDPRO) as a proxy for GDP, and the Consumer Price Index (CPI) over the period 2010–2019. After testing for stationarity and cointegration, we estimate a VAR model on the differenced series and apply a Cholesky decomposition to identify structural shocks. Our results indicate that only the responses to own-shocks are statistically significant, with no clear evidence of cross-variable interactions. Variance decomposition confirms that variations in each variable are primarily driven by their own shocks rather than external influences. These findings suggest that, contrary to some existing literature, short-term oil price fluctuations do not significantly influence unemployment in New Mexico.

Keywords: Oil prices; Unemployment rate; SVAR model; New Mexico; Energy sector; Time series analysis

1 Introduction

Following the breakthrough of unconventional hydrocarbons such as tight oil or shale gas, the United States of America (USA) has strengthened its leading position in world production. Outpacing Saudi Arabia and Russia, US oil production increased by 2.2 times between 2009 and 2021, while gas production rose by 71% over the same period (EIA). This increase in energy production is concentrated in a few key states, such as Texas, New Mexico or Pennsylvania. New Mexico is the second largest producer of oil behind Texas. Producing 1.8 million barrels per day, New Mexico produce as much as a country like Norway. Additionnaly, New Mexico comes in 5th position when it comes to gas production and produce as much as a country like the United Kingdom. All of these things make New Mexico an energy state. Energy states are states that have a relatively high share of the country's energy production, while also having a high share of their revenues derived from energy production[1].

In such states, energy-related matters can be sensitive. With major consequences for the environment and health, fracking methods have become the subject of intense discussion. Those concerns were a source of tension during the last American elections. For instance, in the swing state of Pennsylvania, many jobs depend on fracking, particularly for the production of shale gas. As the Democratic candidate Kamala Harris once advocated a ban on these production methods, the new Republican president Donald Trump took the opportunity to defend the fossil fuel industry, while insisting that there would be no job losses[2].

In 2022, over 65,000 people were employed in the energy sector, representing 8% of total employment in New Mexico. This does not take into account the many indirect jobs supported by the

[1] Laurent Carroué, *Le boom des hydrocarbures non conventionnels dans le Bassin permien (Texas et Nouveau-Mexique, États-Unis)*, Géoconfluences, 2022

[2] France Info, *Présidentielle Américaine : En Pennsylvanie, Le Gaz de Schiste Divise Les Électeurs*, 2024

energy industry, particularly in the transport, construction and equipment manufacturing sectors. In addition, in 2023, New Mexico received more than $4 billion in direct revenue from oil and gas production, which represents approximately 13% of the total tax revenue collected[3]. These revenues directly influence public spending on education, infrastructure and healthcare, which in turn have an impact on the creation and maintenance of jobs in non-energy sectors.

In a state like New Mexico, which is fairly dependent on fossil fuels, we can ask ourselves whether the price of oil might have an impact on the labour market, and more specifically on the unemployment rate. Representing the number of unemployed as a percentage of the working population, the unemployment rate is one of the most important macroeconomic indicators. Many articles have studied the effects of oil shocks on the unemployment rate at state level. Literature results differ depending on the terrain used. For example, Soytas, 2017 suggests that oil prices do not influence the unemployment rate in Texas. These conclusions are supported by Karaki, 2018 which reveals that an adverse supply shock in the crude oil market leads to an increase in unemployment in almost all US states, with the exception of Texas, Colorado and Wyoming. However, Brown and Yücel, 2013 found that the only states that tend to benefit from higher oil prices are New Mexico, West Virginia, Texas, Louisiana, Alaska, North Dakota, Oklahoma and Wyoming. More generally, it would appear that the impact of oil prices on the unemployment rate differs according to the type of macroeconomic shock. Karaki, 2018 point out that an increase in oil prices caused by an unexpected reduction in world oil supply has very different effects from an increase in oil prices caused by an unexpected increase in economic activity.

In this context, we can investigate the impact that a shock - upwards or downwards - in the price of oil could have on the level of unemployment in New Mexico. To achieve this, we employed a four-variable structural vector autoregressive model (SVAR) with the impulse response function (IRF) and time-series data for the period 2010-2019. First, we will present the data used. We will then review the methodology and methods used. Finally, we will use this theoretical framework to try to provide empirical explanations for the relationship that may exist between the price of oil and the unemployment rate in New Mexico.

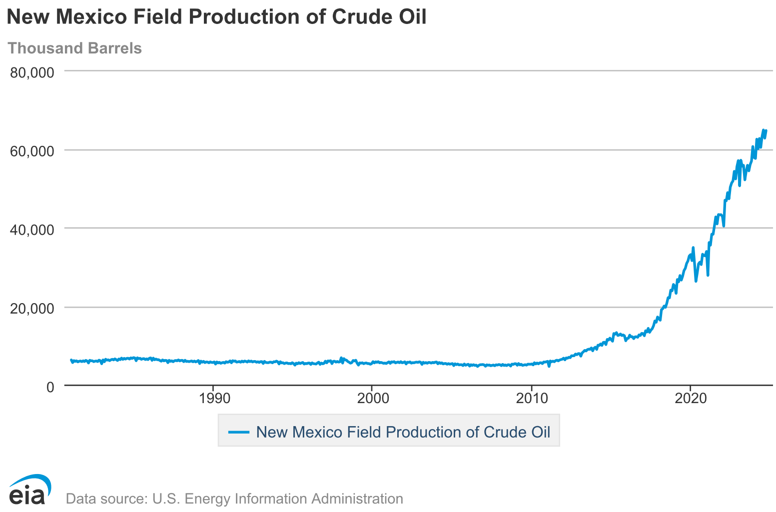
2 Data

Although it lacks of emprical validy, Phillips Curve is still one of the main framwork used by policy makers and economist to determine structural determinants of inflation in the US (Haschka, 2024). According to this theory, there is a negative relationship between inflation and the unemployment rate: the lower inflation, the higher unemployment. It was therefore essential to include this variable in our modelling. When it comes to working on the determinants of the unemployment rate, Gross Domestic Product (GDP) is an indispensable macroeconomic indicator. According to Okun's law, a negative relationship would exist between the growth rate and the unemployment rate. Although this law has often been contested and invalidated, it nevertheless remains an important theoretical foundation for economic science. Because we use monthly indicators, the industrial production index (INDPRO) we'll be used as a proxy for estimating GDP.

Figure 1 shows the evolution of oil production in New Mexico since the 1960s. As we can see, production was relatively low and stable from 1960 to 2010. As mentioned in the introduction, it took the emergence of unconventional oil for New Mexico to become a major oil producer. For this study, we first selected the entire period from 1960 to the present day. However, some of the restrictive assumptions of the VAR models did not allow us to go any further in the analysis, which would have been a problem. This is why we had to reduce the range of analysis. Secondly, we tried to cover the period from 2010 to the present day, to capture the sharp increase in production. However, the last few years (post-covid) have introduced a great amount of volatility into the four variables chosen for this study, once again knocking out some key assumptions. In addition, this allows us to avoid the potential biases associated with the subprime crisis and the COVID 19 pandemic. As a result, our analysis will focus on the period from 2010 to 2019. As the data are on a monthly basis, we have 108 observations.

[3] Finance Facts: Oil and Gas Revenue - New Mexico Legislature

Figure 1: **New-Mexico Field Production of crude oil**



Figures and tables that will be presented below were produced by the authors using data collected from the Federal Reserve Economic Data (FRED)

2.1 Descriptive analysis

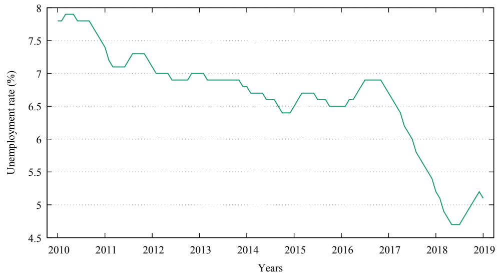
Figure 2 provides a dynamic picture of the economic indicators, highlighting distinct trends and relationships. The sustained fall in the NMUR (Figure 2a) between 2010 and 2018 might reflects the prolonged recovery of the labour market from the Great Recession of 2008. While the initial phase of this decline was fuelled by expansionary monetary policies and fiscal stimulus, recent years have been marked by structural improvements in employment conditions (Blanchard, 2018). However, intermittent plateaus in the unemployment rate may indicate periods of slower job creation, possibly influenced by sectoral adjustments or external shocks.

CPI's trajectory suggests an initial period of inflationary pressure, followed by greater stabilisation after 2014 (Figure 2b). The initial rise in inflation could be attributed to the recovery in aggregate demand, while its later moderation coincides with the collapse in oil prices. Given the significant weight of energy costs in consumer price indices, the sharp fall in WTI prices - observed between 2014 and 2016 - probably helped to ease inflationary pressures over this period.

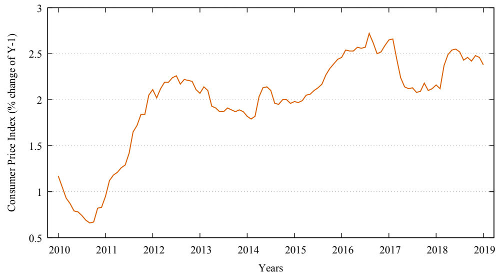
INDPRO shows a long-term upward trend, reflecting strong industrial growth (Figure 2c). This growth is consistent with broader macroeconomic conditions, including rising productivity and a gradual improvement in world trade. However, temporary slowdowns in industrial production may reflect external uncertainties, such as trade tensions or financial market volatility.

Finally, WTI prices are fluctuating wildly (Figure 2d), with the sharp fall observed around 2015 reflecting a supply shock. Increased shale production in the US, coupled with OPEC's decision to maintain high production levels, led to a supply surplus which exerted downward pressure on prices. This episode illustrates the wider macroeconomic implications of oil price volatility, influencing inflation expectations, industrial costs and employment in energy-intensive sectors (Baumeister and Kilian, 2016).

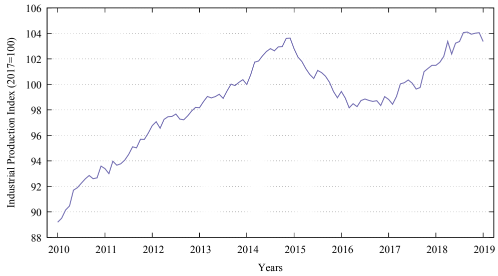
Figure 2: **Time series plots**



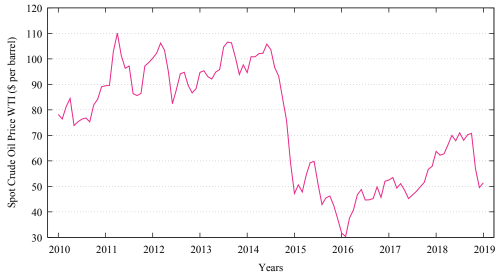
(a) NMUR



(b) CPI



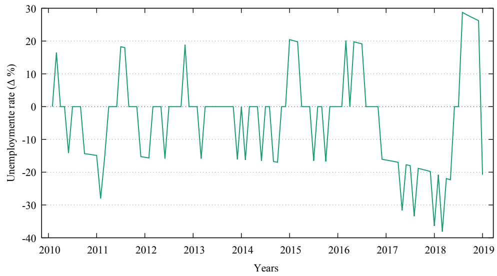
(c) INDPRO



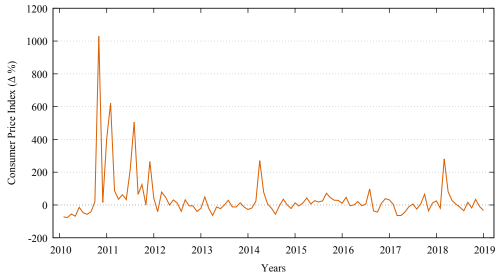
(d) WTI

Analysis of the percentage changes in the economic indicators provides additional indications of their volatility and possible structural changes over the period studied (Figure 3). The unemployment rate (NMUR) shows strong fluctuations, particularly around 2018, confirming the presence of significant cyclical effects that may be linked to changes in labour market conditions. The Consumer Price Index (CPI) shows extreme variations, particularly in the early 2010s, which may reflect inflationary shocks . The index of industrial production (INDPRO) shows notable volatility, with a pronounced spike in April 2018, reinforcing the outlier previously observed. Finally, crude oil (WTI) prices show significant variations, particularly around 2016, likely reflecting the consequences of the oil price collapse from 2014 to 2016 and subsequent market adjustments.

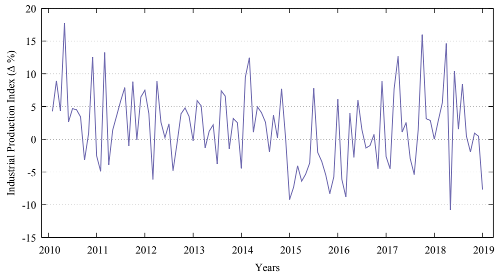
Figure 3: **Time series plots : Variation (Δ%)**



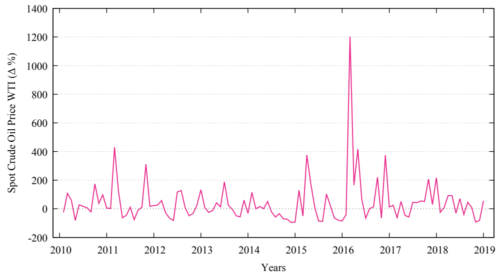
(a) NMUR



(b) CPI



(c) INDPRO



(d) WTI

Table I summarizes the key distributional characteristics of four economic indicators, revealing varying degrees of stability, dispersion, and underlying economic implications.

Among the indicators, industrial production (INDPRO) stands out as the most stable, with a remarkably low coefficient of variation (0.037), reflecting its role as a steady measure of economic activity. Its nearly symmetrical distribution (skewness = -0.687) and slightly flattened tails (kurtosis = -0.165) suggest that industrial production is less prone to extreme fluctuations, likely tied to the gradual and incremental nature of changes in industrial output.

In contrast, oil prices (WTI) exhibit the highest volatility, as indicated by a coefficient of variation of 0.304 and a wide range (30.32 to 110.04). This high dispersion underscores the sensitivity of oil markets to global supply-demand shocks, geopolitical tensions, and macroeconomic uncertainties. The almost symmetrical distribution (skewness = -0.141) and pronounced platykurtic nature (kurtosis = -1.402) suggest frequent but moderate price fluctuations rather than extreme outliers.

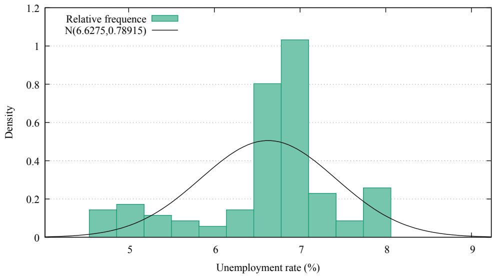
The unemployment rate in New Mexico (NMUR) and the consumer price index (CPI) exhibit intermediate levels of variability, though their distributional patterns reveal distinct economic behaviors. NMUR, with a modest coefficient of variation (0.119), suggests a relatively stable labor market over the period, despite negative skewness (-0.924) indicating a tendency toward lower unemployment levels. In contrast, CPI displays greater dispersion (C.V. = 0.267), with a negatively skewed distribution (-1.105) that points to periods of below-average price levels. This pattern may reflect deflationary pressures or subdued inflationary dynamics during the observed period.

Table I: **Descriptive statistics for key variables**

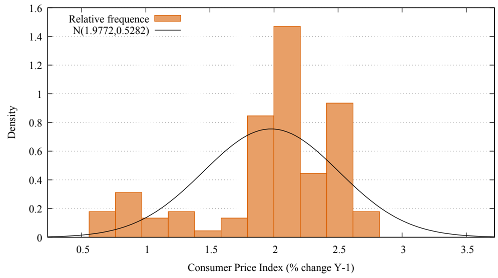
Variable	Min.	Median	Mean	Max.	Std. Dev.	C.V.	Skewness	Ex. Kurtosis
NMUR	4.700	6.800	6.628	7.900	0.789	0.119	-0.924	0.462
CPI	0.660	2.100	1.977	2.720	0.528	0.267	-1.105	0.388
INDPRO	89.190	99.040	98.691	104.100	3.627	0.037	-0.687	-0.165
WTI	30.320	76.370	73.964	110.040	22.457	0.304	-0.141	-1.402

The histograms reinforce the findings from the descriptive statistics. The New Mexico unemployment rate (NMUR) and the consumer price index (CPI) exhibit negatively skewed distributions, indicating that lower values occur more frequently than higher ones. This asymmetry suggests that periods of low unemployment and moderate inflation were more common throughout the sample. The industrial production index (INDPRO) presents a more symmetric distribution, reflecting its relative stability over time. In contrast, West Texas Intermediate (WTI) crude oil prices display a broad dispersion and a platykurtic distribution, signaling a higher degree of variability. This finding is consistent with the well-documented volatility of oil prices, driven by fluctuations in global supply and demand, geopolitical events, and financial market speculation (Hamilton, 2013).

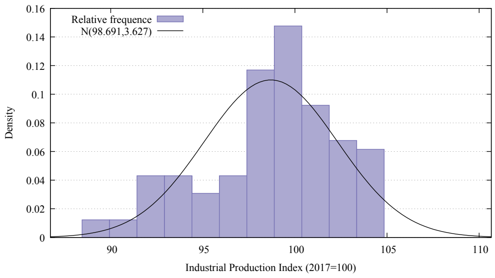
Figure 4: **Histograms**



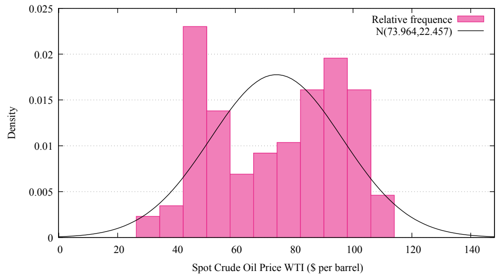
(a) NMUR



(b) CPI



(c) INDPRO



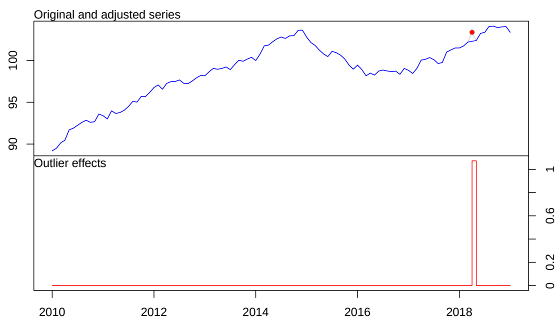
(d) WTI

2.2 Outlier analysis

The identification and treatment of outliers are crucial steps in the analysis of time series.We adjust outliers only if they do not stem from a justifiable historical event. These values, which deviate significantly from the other observations in the series, can be the result of measurement errors, unusual events or anomalies in the data. In order to identify and handle we will use the `tso()` function from R's `tsoutliers` package.

Time series analysis reveals that an outlier, identified as an **Additive Outlier (AO)**, is present in the Industrial Production Index (INDPRO) in April 2018 (Figure 5 below). This anomaly corresponds to an abnormal rise in INDPRO over this month. The event does not seem to be linked to any particular economic event. We are therefore correcting this outlier in order to continue the analysis.

Figure 5: **Outliers identification on INDPRO**



2.3 Seasonality analysis

Detecting seasonality in time series is an essential step in econometric analysis, as it enables us to identify and understand the periodic variations that affect the data. These seasonal fluctuations, often linked to climatic, social or economic factors, can mask the underlying trends in the series and distort the interpretation of the results. By ignoring seasonality, there is a risk of coming to incorrect conclusions about the relationships between variables and producing inaccurate forecasts.

Table II: Seasonality tests

Tests	Variables			
	NMUR	CPI	INDPRO	WTI
Panel A: Non parametrics tests				
Kruskal-Wallis	No seasonality(p>0.05)			
Test de Friedman	No seasonality(p>0.05)			
Panel B: Time series specifics tests				
Webel-Ollech	No seasonality(p>0.05)			
Test QS	No seasonality(p>0.05)			
Variables Saisonnières	No seasonality(p>0.05)			

Tests of seasonality (*Table* II) applied to macroeconomic variables (NMUR, CPI, INDPRO and WTI) reveal a systematic absence of significant seasonal components. This conclusion is supported by five separate statistical tests, each approaching the question of seasonality from a different methodological angle. This convergence of results across different statistical methodologies suggests that these macroeconomic variables can be analysed without the need for seasonal adjustments.

2.4 Stationarity analysis

Stationarity is an essential property of time series in econometrics. A series is considered stationary when its statistical characteristics, such as the mean, variance and autocorrelation structure, remain constant over time. This property is fundamental to the validity of many econometric models, particularly VAR models, which generally assume that the time series analysed are stationary.

The use of non-stationary series within models designed for stationary data can lead to biased estimates and misleading conclusions, a phenomenon known as fallacy regression. Non-stationarity can give the illusion of significant relationships between variables where none actually exist.

However, some methods allow non-stationary series to be modelled under specific assumptions. Co-integration is a particular case where several non-stationary series share a long-term equilibrium relationship. In this context, VECM (Vector Error Correction Model) models offer an appropriate solution: they integrate short-term dynamics while taking into account long-term relationships between co-integrated variables. Although stationarity is a key requirement in many cases, models adapted to co-integrated series make it possible to exploit the information contained in non-stationary time series.

Table III: Stationarity tests

Tests	Variables			
	NMUR	CPI	INDPRO	WTI
Panel A: Conventional unit root tests				
Dickey-Fuller	Non-stationary (p <0.05)			
Dickey-Fuller with constant	Non-stationary (p <0.05)			
Dickey-Fuller with constante and trend	Non-stationary (p <0.05)			
KPSS	Non-stationary (p >0.01)			
Elliott-Rothenberg-Stock (DF-GLS)	Non-stationary (p <0.05)			
Panel B: Unit root test with structural rupture				
Zivot-Andrews	Non-stationary (p <0.05)			
Structural breaks	76	98	49	58

Table III presents the results of the stationarity tests on four time series (NMUR, CPI, INDPRO, WTI). All the tests (Dickey-Fuller, Dickey-Fuller with constant and trend, KPSS, and Elliott-Rothenberg-Stock) indicate that the series are non-stationary (p >0.05 or p <0.01), suggesting changing trends or structures over time. The Zivot-Andrews test confirms non-stationarity, with structural breaks identified at different points for each series (76 for NMUR, 98 for CPI, 49 for INDPRO, 58 for WTI). Thus the series studied are non-stationary, with possible structural breaks. After first differencing the series, they all become stationary (*see Table* VII).

3 Model theory presentation

3.1 Vector autoregression (VAR)

The vector autoregression (VAR) model is a generalisation of autoregressive (AR) models to multivariate systems, introduced by Christopher Sims in 1980. It is used to analyse multivariate time series and to understand how current observations of one or more variables are related to their own past observervartions as well as to past observations of the other variables included in the system. Unlike traditional structural models, the VAR model does not require an explicit distinction between exogenous and endogenous variables, making it a powerful tool to investigate complex relationships between economic variables.

The k-dimensional VAR(p) model is written as :

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \ldots + \mathbf{A}_p\mathbf{y}_{t-p} + \epsilon_t$$

Where :

- $\mathbf{y}_t$ a vector of k variables at date t.
- $\mathbf{c}$ a vector of constants.
- $\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_p$ a matrix of $k \times k$ dimensions representing the effects of past values of variables on their current values.
- ϵ_t is a vector of error terms at date t, representing the random shocks affecting the system.

Before estimating a VAR model, it is essential to determine the number of lags p to include in the model. This parameter influences the model's ability to capture system dynamics. The number of lags can be selected using information criteria such as AIC, BIC or HQ, generally preferring a parsimonious structure.

Once the VAR model has been estimated, it is important to validate its quality and relevance. This begins with a check on the model's stability. A model is considered stable when the effects of past shocks diminish over time. This stability can be assessed by examining the eigenvalues of the companion matrix: if they are all less than 1 in absolute value, the model is stable. An analysis of the residuals is also necessary to ensure that they behave like white noise. More specifically, the residuals must be uncorrelated, normally distributed and homoscedastic. These assumptions can be tested using statistical methods such as the Portmanteau test for autocorrelation, the Jarque-Bera test for normality and the ARCH test for heteroscedasticity.

The VAR model is a versatile tool with many applications. It can be used to forecast the future evolution of variables in a system. Thanks to its ability to capture the dependency relationships between variables, the model generates relevant multivariate forecasts. In addition, the analysis of impulse response functions makes it possible to visualise the dynamic impact of a shock on a given variable and to study the way in which this shock propagates to other variables over time. Finally, forecast error variance decomposition (FEVD) is another important application. It quantifies the contribution of each variable to the forecast error variance of the other variables.

3.2 Vectoriel error correction model (VECM)

The Vector Error Correction Model (VECM) is an extension of the VAR model that takes into account cointegration between the variables in the system. Cointegration implies that there is a stable long-term relationship between the variables, even though they may deviate from this relationship in the short term. The VECM allows us to model both the short-term dynamics and the long-term equilibrium relationship between the variables. Statistical tests such as the trace test and the maximum eigenvalue test can be used to detect cointegration. If no cointegrating relationship is detected during the initial analysis, it is advisable to abandon the VECM in favour of estimating a classic VAR model, which is more appropriate in this context. The VECM model is written as follows:

$$\Delta \mathbf{y}_t = \mathbf{c} + \mathbf{\Pi} \mathbf{y}_{t-1} + \sum_{i=1}^{p-1} \mathbf{\Gamma}_i \Delta \mathbf{y}_{t-i} + \epsilon_t$$

Where :

- $\Delta \mathbf{y}_t$ is the first difference in the vector of variables at date t.
- $\mathbf{\Pi}$ eis a matrix of coefficients that captures the long-term cointegration relationship between the variables.
- $\mathbf{\Gamma}_i$ are matrices of coefficients that capture the short-term relationships between variables.
- $\mathbf{y}_{t-1}$ is the vector of variables at date $t-1$.
- ϵ_t is a vector of error terms at date t.

3.3 Strucural Vector autoregression (SVAR)

The Structural Vector Autoregression (SVAR) model is a structural representation of the VAR model. Unlike the reduced-form VAR, which reveals nothing about the structure of the economy, the SVAR enables restrictions to be imposed on the VAR coefficients in order to identify and interpret the structural shocks affecting the system. The SVAR(p) structural model with k dimensions and p lags is written in the form :

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}_0 + \mathbf{B}_1 \mathbf{y}_{t-1} + \mathbf{B}_2 \mathbf{y}_{t-2} + \ldots + \mathbf{B}_p \mathbf{y}_{t-p} + \epsilon_t$$

Where :

- $\mathbf{A}$ is a matrix of coefficients that captures the instantaneous relationships between the variables
- $\mathbf{B}_i$ are matrices of coefficients that capture the dynamic relationships between variables.
- ϵ_t represents the structural shocks to the system.

To estimate the structural model, we first need to estimate its reduced form:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1 \mathbf{y}_{t-1} + \mathbf{A}_2 \mathbf{y}_{t-2} + \ldots + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{u}_t$$

Which can be rewritten as

$$\mathbf{y}_t = \mathbf{c} + \mathbf{C}_1 \mathbf{y}_{t-1} + \mathbf{C}_2 \mathbf{y}_{t-2} + \ldots + \mathbf{C}_p \mathbf{y}_{t-p} + \mathbf{A}^{-1} \epsilon_t$$

Where :

- $\mathbf{u}_t = \mathbf{A}^{-1} \epsilon_t$ represents structural errors.

The identification of an SVAR model is based on the restrictions imposed on the A and B matrices. These restrictions, based on economic theory, are used to distinguish structural shocks from purely random shocks. Two main approaches are commonly used to establish these restrictions. The first approach, the Cholesky decomposition, imposes short-term restrictions. It is based on the assumption that certain variables have no immediate impact on others. This method requires variables to be classified from the most exogenous to the most endogenous. The second approach, known as the Blanchard-Quah method, focuses on long-term restrictions. It postulates that certain shocks do not have a permanent effect on certain variables, which provides a better understanding of the long-term dynamics of the system.

4 Model estimations and results

4.1 Identifying cointegration relationships

We observed that the four variables under study do not satisfy the stationarity assumptions required for the application of a VAR model. As such, applying a VAR model to the level series would risk producing spurious regressions. However, we determined that the three series are integrated of order one ($I(1)$, see Table VII). This allows us to investigate potential cointegration relationships.

As a first step, we identify the appropriate lag length for the model. To this end, we estimate a VAR model on the level series. Based on the four information criteria, 1 and 2 lags are suggested (Table IV below).

Table IV: **Selection of the number of lags for the VAR model**

Criterion	**AIC(n)**	**HQ(n)**	**SC(n)**	**FPE(n)**
Optimal lag	2	2	1	2

The initial serial correlation test was conducted with a lag order of 1. However, since the test results indicate significant residual autocorrelation ($pvalue = 4.14e-07$), the model was iteratively adjusted by increasing the lag order to 2 to address this issue. This adjustment follows the principle of parsimony, ensuring the model remains as simple as possible while adequately addressing autocorrelation issues.

Consequently, we estimate a VAR(2) model and proceed with tests to assess its adequacy. All eigenvalues lie within the unit circle, indicating that the model is stable. Subsequently, we test for the normality, autocorrelation, and homoscedasticity of the residuals. The results of these tests are presented in Table V.

Table V: **Diagnostic tests of the VAR model**

Tests	H_0 **hypothesis on residuals**	**P-value**
Jarque-Bera	Normality	0.48
Portmanteau	No autocorrelation	0.17
ARCH	Homoscedasticity	0.55

All tests are accepted at the 1% risk threshold. We have therefore determined the number of lags (2) that we include in the Johansen trace test. The trace test and the lambda-max test are statistical tools used to identify the presence of cointegration between non-stationary time series. These tests serve as a preliminary step before estimating a Vector Error Correction Model (VECM). The procedure involves first estimating a VAR model on the series in levels and then applying the trace or lambda-max test to the residuals of this VAR. When cointegration is detected, it indicates the existence of a stable long-term relationship between the variables, making a VECM the appropriate modeling approach to capture this relationship. Alternatively, if no cointegration is found, it is more appropriate to estimate a VAR model on the differenced series, as the absence of cointegration suggests that any apparent relationship between the variables is spurious. Both the trace test and the lambda-max test are complementary methods that help determine the number of cointegration relationships. By examining the cointegration matrix of the VAR model, these tests identify its rank, which corresponds to the number of long-term equilibrium relationships between the variables.

Table VI: **Johansen cointegration test results**

H_0	Eigen value	Statistic	Critical values 10%	5%	1%	Decision
Panel A : Trace test						
$r \leq 3$	0.002	0.19	6.50	8.18	11.65	Non rejected
$r \leq 2$	0.058	6.56	15.66	17.95	23.52	Non rejected
$r \leq 1$	0.065	13.80	28.71	31.52	37.22	Non rejected
$r = 0$	0.204	38.24	45.23	48.28	55.43	Non rejected
Panel B : Maximum eigenvalue test						
$r \leq 3$	0.002	0.19	6.50	8.18	11.65	Non rejected
$r \leq 2$	0.058	6.37	12.91	14.90	19.19	Non rejected
$r \leq 1$	0.065	7.23	18.90	21.07	25.75	Non rejected
$r = 0$	0.204	24.44	24.78	27.14	32.14	Non rejected

Note : The tests include a linear trend. r represents the number of cointegrating relationships.

The cointegration between the four variables was analysed using two complementary Johansen tests (Table VI). The trace test examines the null hypothesis that there are at most r cointegrating relationships, while the maximum eigenvalue test specifically tests the hypothesis of r versus $r+1$ cointegrating relationships. Trace test results show that for $r = 0$, the statistic (38.24) is below the critical values of 45.23 (10%), 48.28 (5%) and 55.43 (1%). Similarly, for $r \leq 1$, $r \leq 2$, and $r \leq 3$, the test statistics (13.80, 6.56, and 0.19 respectively) are systematically lower than their critical values corresponding to the three standard thresholds. The maximum eigenvalue test supports these conclusions. The statistic for $r = 0(24.44)$ is below the critical thresholds of 24.78 (10%), 27.14 (5%) and 32.14 (1%). The statistics for the higher ranks follow the same pattern, with values (7.23, 6.37, and 0.19) always below the associated critical values. These results suggest the robust absence of a long-term equilibrium relationship between the variables studied. The concordance between the two tests supports the validity of this conclusion, implying that the dynamics of these macroeconomic variables are independent in the long term, despite their possible interactions in the short term.

4.2 Estimation of a VAR model

We were unable to identify any long-term relationships between the variables and therefore focused on analyzing short-term dynamics using a VAR model. The results of the various stationarity tests indicate that all four variables are non-stationary. However, after being differentiated, they become stationary (Table VII).

Table VII: **Stationarity tests**

Tests	**Variables** NMUR	CPI	INDPRO	WTI
Panel A: Conventional unit root tests				
Dickey-Fuller	Stationary ($p < 0.05$)			
Dickey-Fuller with constant	Stationary ($p < 0.05$)			
Dickey-Fuller with constant and trend	Stationary ($p < 0.05$)			
KPSS	Stationary ($p > 0.05$)			
Elliott-Rothenberg-Stock (DF-GLS)	Stationary ($p < 0.05$)			
Panel B: Unit root test with structural break				
Zivot-Andrews	Stationary ($p < 0.05$)			
Structural breaks	76	98	49	58

4.2.1 Model stability

The next step involves selecting the optimal lag length for the $VAR(p)$ model. All information criteria unanimously suggest a single lag (Table VIII). Accordingly, a $VAR(1)$ model is estimated. Finally, diagnostic tests are conducted on the residuals to assess the adequacy of the model.

Table VIII: **Selection of the number of lags for the VAR model**

Criterion	**AIC(n)**	**HQ(n)**	**SC(n)**	**FPE(n)**
Optimal lag	1	1	1	1

Our objective is to estimate a stable VAR model, which requires the condition of stationarity to be satisfied. This is achieved when all eigenvalues are less than 1. As this condition is met, the model is confirmed to be stable.

4.2.2 Residual analysis

We assess the residuals of the VAR(1) model to ensure they meet the necessary statistical assumptions. Normality is evaluated using the Jarque-Bera test, where the null hypothesis corresponds to non-normal residuals. To examine the absence of autocorrelation in the residuals, we apply the Portmanteau test. Lastly, homoscedasticity is tested using the ARCH test. The results of these diagnostics are summarized in Table IX.

Table IX: **Diagnostic tests on VAR modelization**

Tests	**H_0 hypothesis on residuals**	**P-value**
Jarque-Bera	Normality	0.0099
Portmanteau	Absence of autocorrelation	0.4488
ARCH	Homoscedasticity	0.2459

Apart from the normality hypothesis, the estimated VAR(1) model satisfies the assumptions of homoscedasticity, and the absence of autocorrelation in the residuals. Based on these results, the reduced-form model can be deemed appropriate.

4.2.3 Granger's Causality

Vector Autoregressive (VAR) models are useful tools for analyzing causal relationships between variables. To assess this, we focus on Granger causality, which posits that one variable is said to cause another if it improves the latter's forecasts. Granger causality is tested using the causality function from the vars[8] package.

Table X: **Causality test results**

Variable	Granger's test		Instant Causality	
	F statistic	p-value	χ^2	p-value
NMUR	0,735	0,531	3,685	0,298
CPI	0,217	0,885	2,198	0,532
INDPRO	0,111	0,954	1,791	0,617
WTI	0,889	0,447	3,786	0,286

The p-value exceeds 0.05 for all variables, indicating that none of the variables in the model Granger-causes the others (Table X). However, it is essential to go beyond Granger causality. Specifically, we can examine the effects of shocks to one variable on the others through impulse response functions. To achieve this, it is necessary to identify the structural form of the model.

4.3 Structural VAR model (SVAR)

In order to identify the structural shocks in our VAR model, we use a Cholesky decomposition, which orthogonalises the residuals of the model by imposing a recursive structure. This method consists of transforming the variance-covariance matrix of the errors into a triangular matrix, which is generally smaller, so that the shocks to the variables appear to be independent of each other. The purpose of this orthogonalization is to isolate the specific effects of each variable in order to better understand the transmission mechanisms of shocks within the economic system. The use of the Cholesky decomposition in this analysis is consistent with an attempt to identify short-term structural shocks, in line with the research problem.

However, the Cholesky decomposition imposes a crucial constraint: the order of the variables must reflect their degree of exogeneity. The variable in the first position is considered to be the most exogenous, as it is only affected by its own contemporaneous shocks. On the other hand, the variable in last position is the most endogenous, because it is influenced by the shocks to all the variables that precede it. Therefore, the hierarchy of variables must be based on rigorous theoretical justification to ensure that the results obtained are economically consistent and interpretable.

Oil prices are largely considered as an exogenous factor in macroeconomic fluctuations. Historical evidence suggests that oil price shocks have had significant effects on economic activity, often preceding economic recessions. Hamilton, 1983 showed that most post-war recessions in the US were preceded by a sharp rise in oil prices, highlighting their role as an exogenous shock (*ibid*). In addition, Barsky and Kilian (2004) have pointed out that oil price fluctuations are largely determined by geopolitical factors and global imbalances between supply and demand, which justifies placing oil prices at the top of the causal hierarchy (Barsky and Kilian, 2004).

GDP[4] follows oil prices in the decomposition, which reflects its sensitivity to energy price shocks. Changes in oil prices affect production costs, consumer purchasing power and investment decisions, all of which determine GDP growth (Hamilton, 1988). Bernanke et al., 1997 have provided empirical evidence that oil shocks contribute significantly to fluctuations in GDP, notably through their effects on monetary policy responses and aggregate demand. This approach implies that GDP is influenced by oil prices but remains an important determinant of labour market conditions and inflation.

The unemployment rate is ranked after GDP because it is largely responsive to economic activity. A fall in GDP generally leads to a reduction in the demand for labour, which in turn leads to an increase in unemployment. Loungani, 1986 has shown that oil shocks have a significant impact on unemployment, particularly in sectors heavily dependent on energy. Similarly, Carruth et al., 1998 found a strong link between the prices of inputs, such as oil, and labour market dynamics, supporting the argument that GDP precedes unemployment in the causal order.

Inflation is considered to be the most endogenous variable in the system. It is influenced by oil prices through production costs, by GDP through demand pressures, and by the unemployment rate through tensions on the labour market (Blanchard and Galí, 2007). Blanchard and Galí, 2007 analysed the impact of oil shocks on inflation and showed that, although the effect weakened over time, it remained significant. Gordon, 1997 highlighted the role of the unemployment rate in explaining inflation through the Phillips curve framework, providing further justification for its placement as the most endogenous variable.

So in our model the matrix is designed as a lower triangular matrix with unrestricted diagonal elements, which implies that each variable can react immediately to its own shocks as well as to the shocks of the variables that precede it in the causal order. In contrast, matrix B, which represents the standard deviations of structural shocks, is specified as a diagonal matrix, reflecting an assumption of independence between the different structural shocks. Each variable is assumed to be affected only by its own structural shock, with shocks assumed to be orthogonal to each other. This identification structure therefore respects the temporal the causal hierarchy suggested by macroeconomic theory, allowing a robust interpretation of the impulse response functions.

[4]As a reminder, we use INDPRO as a proxy of GDP

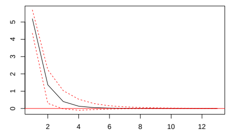
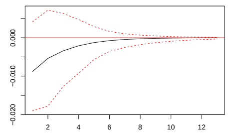
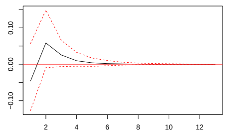
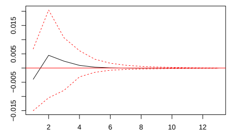
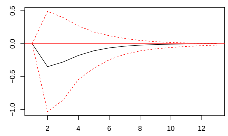
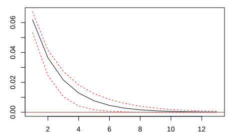
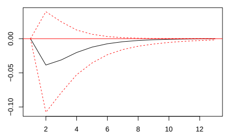
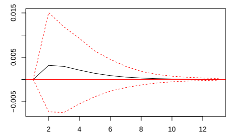
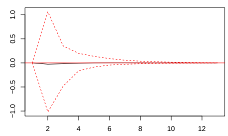
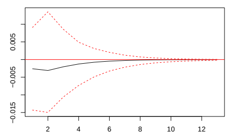
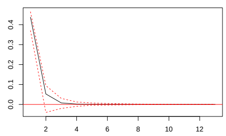
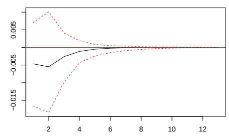
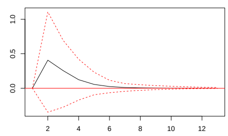
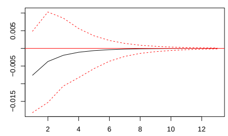
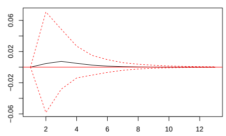
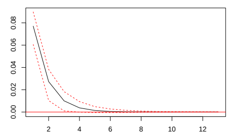
	Response on WTI	Response on NMUR	Response on INDPRO	Response on CPI
Impulsion on WTI				
Impulsion on NMUR				
Impulsion on INDPRO				
Impulsion on CPI				

Table XI: **SVAR model response functions**

Analysis of the impulse response functions (IRFs) derived from our SVAR model (Table XI) highlights several significant dynamic relationships. It should be noted that all these IRFs were generated using a bootstrap method with a confidence interval of 95%, based on 100 iterations.

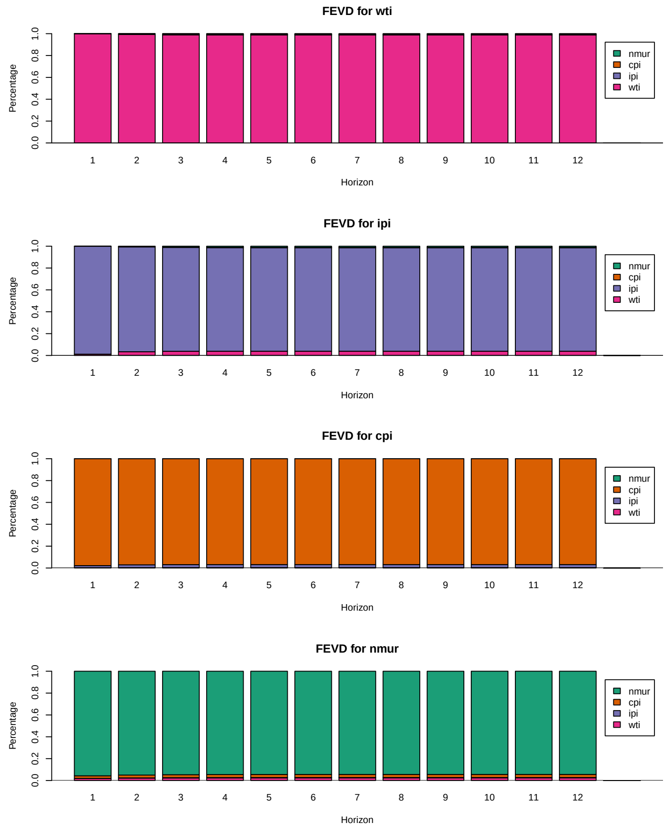
The estimates reveal that only the responses to eigen-shocks, represented on the main diagonal of the IRF matrix, are statistically significant, and only within relatively short time horizons. These are the only impulse functions that do not contain the x-axis (value 0) in the confidence interval.

The oil price reacts significantly to its own shock for approximately three months, with a pronounced initial effect that quickly dissipates. The unemployment rate shows significant persistence in response to its own innovations over a horizon of around five months. The industrial production index shows a significant response to its own shocks over a particularly short period of around one and a half months. As for inflation, its response to its own innovations remains significant for around three months before losing its statistical significance.

Estimation of the cross-relationships between variables, represented by the off-diagonal elements of the IRF matrix, reveals no statistical significance, as their confidence intervals systematically include the value zero. This lack of significance suggests a potential limitation in the model's ability to capture interactions between the macroeconomic variables under consideration.

The econometric model raises a number of methodological issues. The amplitude of the confidence intervals and the behaviour of the central impulse functions, which occasionally exceed these intervals, suggest problems with the non-normality of the residuals. These observations suggest that the SVAR model needs to be re-specified in order to improve its statistical robustness. For a more detailed interpretation of the impulse response functions, it is useful to examine the variance decomposition (Figure 6).

Figure 6: **Variance decomposition of the SVAR using the Cholesky decomposition**



The results obtained from the SVAR model, based on the Cholesky decomposition, reveal that the variations in each variable are largely explained by their own shocks, while the influence of exogenous shocks from other variables remains limited. This observation is consistent with the impulse response functions previously estimated (Figure XI), which show that only internal shocks have a significant impact. Furthermore, these results are in line with those of the Granger causality tests (Table X), which did not identify any direct causal relationships between the variables analysed.

5 Conclusion

This study investigated the short-term impact of oil price fluctuations on the unemployment rate in New Mexico, a state heavily reliant on the energy sector. To address this, we employed a four-variable structural vector autoregressive (SVAR) model using monthly time series data from 2010 to 2019. The model incorporated the West Texas Intermediate (WTI) crude oil price, the New Mexico unemployment rate (NMUR), the industrial production index (INDPRO) as a proxy for GDP, and the Consumer Price Index (CPI).

Our analysis began by assessing the stationarity of the time series. The results indicated that all four series were non-stationary in their levels but became stationary after first differencing. We subsequently tested for cointegration among the variables, but no long-term equilibrium relationships were found. Therefore, we focused on the short-term dynamics using a VAR model on the differenced data. After selecting the optimal lag length, we conducted diagnostic tests on the residuals, confirming the suitability of the reduced-form VAR(1) model. We then implemented a Cholesky decomposition to identify structural shocks and interpret the impulse response functions, placing oil prices as the most exogenous variable, followed by GDP, unemployment rate, and finally, inflation as the most endogenous. The key findings of this study, based on the SVAR model, revealed that only the responses to own-shocks were statistically significant within relatively short time horizons. Also, the cross-relationships between variables has not given any statistically significant results, suggesting a potential limitation in the model's ability to capture interactions between these macroeconomic variables. Furthermore, variance decomposition showed that variations in each variable are largely explained by their own shocks.

These findings contrast with some of the existing literature, which suggests a significant influence of oil price shocks on unemployment rates at the state level. For instance, while some studies suggest that oil prices do not affect unemployment in Texas, others indicate that specific states, including New Mexico, benefit from higher oil prices. Our results suggest that, over the period of analysis (2010-2019), the short-term impact of oil price fluctuations on the New Mexico unemployment rate was not significant. This could be due to the specific period analyzed or the methodology employed in this research.

This study is subject to several limitations. Firstly, the SVAR model uses a Cholesky decomposition, which is very sensitive to the ordering of variables. Although we used theoretical justifications, the variable ordering could affect the results. Also, the model may be limited by the assumption of linear relationships between variables and the omission of other relevant factors, like geopolitical events, that may be influencing the variables.

Future research should focus on addressing these limitations. Possible directions for improvement could include using alternative structural identification approaches, such as the Blanchard-Quah method to impose long-term restrictions. Employing other model specifications such as a Markov-switching model to test for possible non-linearities might also yield better results. Furthermore, one could expend the analysis by including a longer period of time and additional variables which could provide a deeper insight into the dynamic links between oil prices and unemployment. Finally, exploring alternative econometric techniques, such as panel data analysis could also improve the robustness and reliability of our study.

un horizon d'environ cinq mois, suggérant une inertie temporaire sur le marché du travail. L'indice de production industrielle a manifesté une réaction significative à ses propres chocs sur une période brève d'environ un mois et demi, tandis que la réponse de l'inflation à ses propres innovations est restée significative pendant environ trois mois.

References

Barsky, R. B., & Kilian, L. (2004). Oil price shocks and the macroeconomy. *Journal of Economic Perspectives*, *18*(4), 115–134.

Baumeister, C., & Kilian, L. (2016). Lower oil prices and the u.s. economy: Is this time different? *Journal of Monetary Economics*, *80*, 42–63. https://doi.org/10.1016/j.jmoneco.2016.02.005

Bernanke, B. S., Gertler, M., & Watson, M. (1997). Systematic monetary policy and the effects of oil price shocks. *Brookings Papers on Economic Activity*, *1997*(1), 91–157.

Blanchard, O. (2018). Should we reject the natural rate hypothesis? *Journal of Economic Perspectives*, *32*(1), 97–120. https://doi.org/10.1257/jep.32.1.97

Blanchard, O., & Galí, J. (2007). *The macroeconomic effects of oil price shocks: Why are the 2000s so different from the 1970s?* (Tech. rep. No. 13368). National Bureau of Economic Research.

Brown, S. P., & Yücel, M. K. (2013). Shale gas and tight oil boom: Us states' economic gains and vulnerabilities. *Council on foreign relations*.

Carruth, A., Hooker, M., & Oswald, A. (1998). Unemployment equilibria and input prices: Theory and evidence from the united states. *The Review of Economics and Statistics*, *80*(4), 621–628.

Gordon, R. J. (1997). The time-varying nairu and its implications for economic policy. *Journal of Economic Perspectives*, *11*(1), 11–32.

Hamilton, J. D. (1983). Oil and the macroeconomy since world war ii. *Journal of political economy*, *91*(2), 228–248.

Hamilton, J. D. (1988). A neoclassical interpretation of macroeconomic fluctuations. *Carnegie-Rochester Conference Series on Public Policy*, *28*, 7–61.

Hamilton, J. D. (2013). Oil prices, exhaustible resources, and economic growth. *Journal of Economic Literature*, *51*(2), 185–218. https://doi.org/10.1257/jel.51.2.185

Haschka, R. E. (2024). Examining the new keynesian phillips curve in the us: Why has the relationship between inflation and unemployment weakened? *Research in Economics*, 100987.

Karaki, M. B. (2018). Oil prices and state unemployment rates. *The Energy Journal*, *39*(3), 25–50.

Loungani, P. (1986). Oil price shocks and the dispersion hypothesis. *The Review of Economics and Statistics*, *68*(3), 536–539.

Soytas, U. (2017). Do oil prices influence unemployment rate in texas? *Available at SSRN 3306963*.