SCIENTIFIC LETTERS

Econometrics Letters Volume (4), 2, 2017, December.

Business Cycle Analysis for the Midland-Odessa Petroplex

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Abstract

A business cycle coincident index (BCI) for the Midland-Odessa region is developed using a dynamic single factor modeling methodology. The model assumes that co-movements of metropolitan economic indicators have a common element that can be summarized as a single underlying and unobservable variable known as the "state of the economy." The model utilizes a Kalman filter smoothing approach which smooths the index across time and across indicators, resulting in index movements that are less pronounced during expansions and recessions. Indicator series used to estimate the Midland-Odessa BCI are: employment, the unemployment rate, real retail sales, and total real wages. The estimated BCI exhibits movements that are correlated with national economic contractions and expansions, movements in oil prices, and an existing Midland-Odessa business cycle index.

Keywords: Regional Business Cycles; Kalman Filter; Coincident Indicators
JEL Codes: C51 ; E32; R15

Doi: 10.5455/ELet.2017.4.2.3

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Acknowledgements

Financial support for this research was provided by El Paso Water, City of El Paso Office of Management & Budget, UTEP Center for the Study of Western Hemispheric Trade, and Hunt Institute for Global Competitiveness at UTEP. Helpful comments and suggestions were provided by Roberto Coronado, Marycruz De León, Jesús Mendoza, Karl Putnam, Tim Roth, and Macie Subia.

1. Introduction

Knowledge regarding current conditions of the Midland-Odessa Petroplex economy is difficult to acquire. Regional stakeholders, such as businesses, local government agencies, and consumers will all benefit from more reliable local economic information. While there are many useful macroeconomic variables that can provide insight to national economic conditions, those data do not always reflect local business conditions (Phillips, 2005). One tool that can be used to gauge metropolitan economic health is a business cycle index (BCI). A BCI is a weighted combination of selected economic variables that can provide insights to the current state of the economy (Phillips and Cañas, 2008).

While Midland and Odessa are two separate metropolitan statistical areas (MSAs), strong economic ties and close geographic proximity intertwine the two MSAs as one metropolitan economy. The Midland-Odessa metropolitan economy is part of the larger Texas Permian-Basin region that contains 20 counties. The Permian Basin economy is driven by the oil and gas industry which sustains over 44,000 jobs. It annually generates \$113.6 billion in economic output (Ewing et al., 2014). Midland-Odessa holds roughly half of the Permian Basin population and is the most densely populated area of the region.

Not surprisingly, Midland-Odessa economic activity is strongly influenced by crude oil price movements. The region experienced rapid expansion during the 1970s and early 1980s due to high oil prices, but lost many of those gains when prices plummeted in 1986 (EIA, 2002). The Petroplex economy was also damaged by the economic downturn and financial market crisis in 2008. The recovery spurred by oil price increases that began in 2009 allowed employment to increase by approximately 50 thousand jobs between 2010 and late 2014. During this same period, the unemployment rate hit a low of 2.8 percent in late 2014 (FRBD, 2017). A significant decline in oil prices after July 2014 caused unemployment to increase throughout the ensuing months.

Broad based measures of the Midland-Odessa economy are relatively scarce. The objective of this study is to develop a business cycle index (BCI) for this metropolitan economy. A dynamic single factor methodology is used to develop the BCI. This method has been successfully employed to estimate business cycle indices for other regions and seems to be well suited toward doing so for the Petroplex, also (Arias et al., 2016; Fullerton and Subia, 2017).

Subsequent sections are as follows. Section two provides a brief review of the evolution of BCI estimation methodologies as well as the more recent Stock and Watson (1991) approach. The third section describes the theoretical model and methodology used. Section four discusses the data employed and the empirical results obtained. Section five summarizes the study and offers concluding remarks.

2. Literature Review

Rudimentary business cycle indexes date from the early 1800s, with interest in the topic intensifying during the 1920s and beyond (Kitchin, 1923). Two key elements were eventually identified to play central roles in the definition of a business cycle: co-movements among the individual indicators and the differentiation between expansions and contractions (Burns and Mitchell, 1946; Diebold and Rudebusch, 1996). The Burns and Mitchell (1946) index was maintained by the U.S. Department of Commerce (USDC) until 1995 (Phillips, 2005).

The Conference Board (CB) now maintains the U.S. coincident index which employs four indicators: employees on nonagricultural payrolls; personal income less transfer payments measured in 1996 dollars; industrial production; manufacturing, wholesale, and retail trade sales in 1996 dollars (CB, 2012). The index is calculated by computing the month-to-month changes of each indicator and then adjusting these monthly contributions to equalize the volatility of each indicator. The "component factor," used to equalize the volatility of the monthly contribution, is inversely related to the standard deviation of the month-to-month changes in each component (CB, 2012).

Stock and Watson (1991) employ an econometric approach to index estimation that provides a statistical rationale for the estimation of indicator indices. The model developed is a parametric version of a single index model proposed by Sargent and Sims (1977). The model assumes that the co-movements of indicators have a common element that can be summarized as a single underlying and unobservable variable, the "state of the economy" (Stock and Watson, 1991). It utilizes a Kalman filter smoothing approach which smooths the index across time and across indicators which results in index movements that are less pronounced during expansions and recessions (Phillips and Cañas, 2008). The single factor model approach produces an index that is highly correlated with the CB coincident index.

Clayton-Matthews and Stock (1998/1999) use the single factor method to estimate coincident and leading indexes for Massachusetts. Five criteria are used to select the specification for the coincident index model. The estimated index should reflect recent economic history as well as the cyclical history of the regional economy. The estimated filter should assign weights on the indicator series that concentrate around a zero lag and each indicator should make a significant contribution to the output index. The one-step ahead forecast error for each indicator should be uncorrelated with itself, the forecast errors of the other indicators, and the other indicators. The output of the Kalman filter should be smooth to reflect the assumed smooth state of the economy. Characteristics of the index should be robust.

Phillips (2005) applies the Stock-Watson model to estimate a coincident index for Texas. The index is estimated using non-farm employment, quarterly real gross state product (RGSP), and unemployment. The growth rate for the index is equal to the weighted average change of the component series in order to make it comparable to a different Texas coincident index estimated using the CB method. One-step ahead forecast errors are tested to assess whether the white noise components of the error terms of each of the indicators are uncorrelated with themselves, forecast errors of other indicators, and each of the other indicators (Clayton-Matthews and Stock, 1998/1999). The new coincident index passes the white noise specification test, but the CB method index does not. Finally, the dynamic single factor Texas index is also found to reliably predict downturns with relatively few false signals and with good timing characteristics (Neftci, 1982).

It should be noted that the dynamic single factor model is not the only modern method for estimating a business cycle index. Other candidates include the Hamilton (1989) regime switching approach, the Terasvirta and Anderson (1992) smooth transition procedure, and the Kim and Nelson (1998) dynamic single factor with regime switching technique. Each of the alternative methods has been shown to provide useful information and insights with respect cycle movements in various economies. The approach deployed in this study has been successfully applied to the development of coincident business cycle indices for other metropolitan economies in Texas. Given that, it makes a logical candidate for estimating a similar gauge for the Midland-Odessa Petroplex.

Phillips and Cañas (2008) use the dynamic single factor method to estimate a coincident index for four border metropolitan economies in Texas. Establishment employment, unemployment rate, real wage, and real retail sales data are deployed as indicators with the average growth rate of real personal income in each respective area used to re-trend the series. More recently, the same methodology, indicators, and re-trending procedure is used by Fullerton and Subia (2017) to estimate a coincident index for the Lubbock metropolitan economy which is located fairly close to Midland-Odessa. To date, the latter metropolitan economy has not been analyzed using these techniques. Material below develops a dynamic single factor model coincident index for the regionally important Petroplex economy.

3. Theoretical Model

Indicator series used to estimate the Midland-Odessa BCI are: employment, unemployment rate, real retail sales, and total real compensation (BLS, 2017a). Because the methodology produces a stationary index, the coincident index is re-trended using the growth rate of real metropolitan personal income. The average growth rate of the index is re-trended as equal to the average growth in real metropolitan personal income over the course of the sample (Phillips and Cañas, 2008). Metropolitan personal income data are obtained from the Bureau of Economic Analysis (BEA, 2017), retail sales data are obtained from the Texas Comptroller of Public Accounts (TCPA, 2016), wage data are obtained from the Texas Workforce Commission (TWC, 2017), and employment data are obtained from the Federal Reserve Bank of Dallas (FRBD, 2017). Data series used in this sample begin in 1990. Indicator series for the coincident index are chosen to represent broad components of the overall economy: consumption (retail sales), income (wages), plus employment and unemployment (production) (Clayton-Matthews and Stock, 1998/1999). Comparability to indicator series used by the Conference Board for the national coincident index was also considered. Other selection criteria for indicator series includes: timeliness, relatively high frequency, and availability across MSAs.

Employment data produced by the Bureau of Labor Statistics (BLS, 2017b,c) are early benchmarked with data from TWC (2016). The data are seasonally adjusted with a two-step seasonal adjustment procedure (Phillips and Nordlund, 2012). Early benchmarking and two-step seasonal adjustments are completed by FRBD (2017). The unemployment rate is seasonally adjusted using the X-12 procedure (BLS, 2017b, c).

Wage and compensation data are seasonally adjusted using the X-12 procedure and adjusted for inflation to first quarter 2016 dollars. Retail sales data are obtained from the Texas Comptroller of Public Accounts. The Standard Industrial Classification (SIC) system was used to measure retail sales prior to 2002. Beginning in 2002, the North American Industry Classification System (NAICS) is used to measure retail sales. In order to avoid the bias that would otherwise occur from combining the two data sets, data prior to 2002 are converted into NAICS using the 2002 NAICS to 1987 SIC concordance provided by the U.S. Census Bureau (USCB, 2002). The data are then seasonally adjusted using the X-12 procedure and adjusted for inflation to first quarter 2016 dollars. Wage and retail sales data are reported quarterly with a lag of about three quarters. Metropolitan personal income is adjusted for inflation to first quarter 2016 dollars. Those data are reported yearly with a lag of two years.

The basic form of the model is:

$$Y_t = \beta + \gamma(L)\Delta C_t + \mu_t \tag{1}$$

$$D(L)\mu_t = \varepsilon_t \tag{2}$$
$$\phi(L)\Delta Ct = \delta + \eta_t \tag{3}$$

To estimate the coincident index, the Stock and Watson (1991) procedure is used. The employment, wage, and retail sales series are first transformed using natural logarithms and then first differenced. The unemployment rate is reported in percentages and is differenced without transformation. The resulting series are then normalized by subtracting respective means and dividing by respective standard deviations. This steps insures $\beta = 0$ in Equation (1) and $\delta = 0$ in Equation (3).

Thus, $Y_t = \Delta X_t$ are the stationary first difference in natural logs of the indicators, C_t is the log of the unobserved state of the economy, and μ_t is the idiosyncratic component of each indicator. $\phi(L)$ is a scalar lag polynomial and $D(L)$ is a lag polynomial matrix, L denotes the lag operator. $\phi(L)$ and $D(L)$ are assumed to have finite orders *p* and *k*, respectively. The disturbance terms μ_t and ε_t are assumed to be serially uncorrelated and this assumption is tested as part of the empirical analysis. It is assumed that all off-diagonal values of the D(L) matrix are equal to zero and that all diagonal values are non-zero numbers, assumptions that are also tested below. This allows the μ_t in different equations to be mutually uncorrelated with each other at all leads and lags.

The scale of the $\gamma(L)$ coefficients is fixed by setting the variance of η to unity, while the timing of the coincident index is fixed by setting all but one of the elements $\gamma(L)$ to zero in one of the indicator equations in Equation (1). One- and two-period lags are included for each indicator so that the variables are allowed to influence the index from zero to two lags (Phillips, 2005). Lags that are not significant at the 5% level are dropped. Significant error terms for each of the univariate equations are determined by examining correlograms and Q-statistics of the residuals estimated for the various lag structures. Autoregressive lags of the coincident index itself may also be added in order to correct for any autocorrelation in the index and reduce month-to-month noisiness.

Equations (1) - (3) form the dynamic single-factor, multiple indicator model (Sargent and Sims, 1977). If the Y_t indicators move in conjunction with the economy, then the common co-movement C_t can be interpreted as the current state of the economy (Stock and Watson, 1991). Equation (1) shows how each of the indicator series contributes to the underlying growth process (Phillips and Cañas, 2008). ΔC is the common co-movements in the growth of the indicators, Y. Equation (2) models the idiosyncratic components of each on the indicator series. The idiosyncratic components, μ, are stationary, mean zero, autoregressive stochastic processes (Clayton-Matthews and Stock, 1998/1999). Equation (3) models the growth of the underlying state of the economy (Phillips and Cañas, 2008). Growth in the state of the economy is modeled as a stationary autoregressive process.

Maximum likelihood estimates of the parameters for Equations (1) - (3) and estimation of the filtered state are obtained by representing Equations (1) - (3) in state space form and using a Kalman filter (Clayton-Matthews and Stock, 1998/1999). As shown in Stock and Watson (1991), the state space equation, also called the transition equation, is formed by combining Equations (2) and (3). Because one objective is to estimate the level of C_t using information up to time t, it is convenient to augment these equations by the identity $C_{t-1} = \Delta C_{t-1} + C_{t-2}$ (Stock and Watson, 1991). The Transition equation is given by,

$$\begin{pmatrix} C_t^* \\ \mu^* \\ C_{t-1} \end{pmatrix} = \begin{pmatrix} \phi^* & 0 & 0 \\ 0 & D^* & 0 \\ Z_c & 0 & 1 \end{pmatrix} \begin{pmatrix} C_{t-1}^* \\ \mu_{t-1}^* \\ C_{t-2} \end{pmatrix} + \begin{pmatrix} Z'_c & 0 \\ 0 & Z'_\mu \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \eta_t \\ \varepsilon_t \end{pmatrix} \tag{4}$$

where $C^*_t = \left(\Delta C_t \Delta C_{t-1} \ldots \Delta C_{t-p+1}\right)'$ $\quad \mu^* = \left(\mu'_t \, \mu_{t-1'} \ldots \mu_{t-k+1'}{}'\right)$

$$\phi^* = \begin{pmatrix} \phi_1 \ldots \phi_{p-1} & \phi_p \\ I_{p-1} & 0_{(p-1)x1} \end{pmatrix}$$

$$D^* = \begin{pmatrix} D_1 \ldots D_{k-1} & D_k \\ I_{n(k-1)} & 0_{(k-1)xn} \end{pmatrix}$$

$$Z_c = \begin{bmatrix} 1 & 0_{1x(p-1)} \end{bmatrix}$$

$$Z_c = \begin{bmatrix} 1 & 0_{1x(p-1)} \end{bmatrix}$$

The asterisk indicates that the variable represents a vector or matrix of variables and is used for notational brevity.

The measurement equation is obtained by writing Equation (1) as a linear combination of the state vector:

$$Y_t = \beta + \begin{bmatrix} \Upsilon Z_c & Z_\mu & 0_{n+1} \end{bmatrix} \begin{bmatrix} C_t^* \\ \mu_t^* \\ C_{t-1} \end{bmatrix} \tag{5}$$

Equation (6) and (7) can be written as

$$\alpha_t = \mu_\alpha + T_t \alpha_{t-1} + R\zeta_t \tag{6}$$

$$Y_t = \beta + Z\alpha_t + \xi_t \tag{7}$$

Where $\alpha_t = (C^*_t{}' \, \mu^*_t{}' \, C_{t-1})'$, $\xi_t = \left(\eta_t \;\; \varepsilon_t{}'\right)'$

The Kalman filter is then applied to the state space representation of the model. Let $\alpha_{t|\tau}$ denote the estimate of α_t based on $(y_1,\ldots,y_\tau)$, let $E[\xi_t \, \xi'_t] = H$, $E[\zeta_t \, \zeta'_t] = \Sigma$ and $P_{t|\tau} = E[(\alpha_{t|\tau} - \alpha_t)(\alpha_{t|\tau} - \alpha_t)']$. Given this notation, the prediction equations for the Kalman filter are:

$$\alpha_{t|t-1} = \mu_\alpha + T_t \alpha_{t-1|t-1} \tag{8}$$

$$P_{t|t-1} = T_t P_{t-1|t-1} T'_t + R\Sigma R' \tag{9}$$

The forecast of Y_t at time t-1 is $Y_{t|t-1} = \beta + Z\alpha_{t|t-1}$ and the updating equations for the filters are:

$$\alpha_{t|t} = \alpha_{t|t-1} + P_{t|t-1} Z' F_t^{-1} v_t \tag{10}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1} Z' F_t^{-1} Z \, P_{t|t-1} \tag{11}$$

where $F_t = E[v_t v_t] = Z P_{t|t-1} Z' + H$ and $v_t = Y_t - Y_{t|t-1.}$

This estimation procedure yields three versions of the state vector: $\Delta C_{t|t-1}$, the prediction estimates; $\Delta C_{t|t}$, the filtered estimates; and $\Delta C_{t|T}$, the smoothed estimates. The prediction estimates, $\Delta C_{t|t-1}$, use information from the prior period to estimate the state of each period (Clayton-Mathews and Stock, 1998/1999). These estimates are used to form the one-step ahead prediction errors, $\hat{\varepsilon}_{t|t-1} = \Delta X_t - \Delta X_{t|t-1}'$ which are based on the initial parameter estimates (Clayton-Mathews and Stock, 1998/1999). These prediction errors are the fitted residuals from Equations (1) and (2), where the estimates for $\Delta C_{t|t-1}$ are used in place of the unobserved ΔC. The one-step ahead prediction errors are later used to test the validity of the assumption that the error terms of the component series are mutually uncorrelated with each other at all leads and lags (Clayton-Mathews and Stock, 1998/1999).

As shown in Equation (3), the Kalman filter models each of the indicator series as left-hand-side variables with the unobserved coincident index on the right hand side. Given this structure, quarterly variables are modeled as a function of current and previous values of the monthly latent series. This allows quarterly data to enter the equations with monthly data. This can be demonstrated by:

$$\Delta X_t = \Upsilon(L)\Omega(L)\Delta C_t + \mu_t \tag{12}$$

where $\Omega(L) = 1 + 2L + 3L^2 + 2L^3 + L^4$ and $\Delta X_t = X_t - X_{t-3}$, with t representing months.

Because the methodology produces indexes that are stationary with unit variances, it is necessary to make two adjustments. First, the variance of the growth rate of the index is scaled to the average variance of the growth rates in the component series. Second, the average growth rate of the index is re-trended to equal the average growth in real metropolitan personal income over the course of the sample (Phillips and Cañas, 2008).

The index is estimated using the Dynamic Single-Factor Model Software (DSFM) package (Clayton-Matthews, 2005). The structure of the model, estimation, and transformation from estimated state of the economy to metropolitan coincident index allows extracting the relevant business cycle signal from potentially noisy data. The following section provides an analysis of the estimated coincident index for the Midland–Odessa Petroplex economy.

4. Empirical Analysis

Table 1 contains descriptions of the indicator series used to estimate the coincident index. Table 2 reports summary statistics for each indicator series during the sample period. The employment indicator reaches a maximum of approximately 179 thousand and has an average of about 120 thousand. The series follows an upward trend and exhibits cyclical movements. The unemployment indicator exhibits pronounced cyclical movements and a slight downward trend. It has a maximum of about 9.6 percent and an average of 5.35 percent. Real retail sales has a maximum of \$2,055 million and an average of \$1,260 million. It follows an upward trend and displays notable cyclical movements. Real total wages has an upward trend, but displays relatively muted cyclical movements in comparison to the other indicators.

Table 1: Variables, Definitions, and Units of Measure

Indicator Series	Definition	Units	Source
Employment	Monthly MSA total non-farm employment, early benchmarked using preliminary releases of the QWEC from the TWC, and two-step seasonally adjusted.	Thousands	Bureau of Labor Statistics; Federal Reserve Bank of Dallas
Unemployment	Monthly MSA total labor force currently unemployed and seeking employment, seasonally adjusted	Percent	Bureau of Labor Statistics; Federal Reserve Bank of Dallas
Real Retail Sales	Quarterly MSA retail sales as defined by NAICS, seasonally adjusted, 2016Q1 dollars	Millions	Texas Comptroller of Public Accounts
Real Total Wages	Quarterly MSA total wages and salaries for all industries, seasonally adjusted and in Q1 2016 dollars. Included in wages are paid leave, bonuses, stock options, tips, and cash value of meals and lodging.	Millions	Texas Workforce Commission

Table 2: Indicator Series Summary Statistics

	Employment	Unemployment	Real Retail Sales	Real Total Wages
Mean	119.77	5.35	$1,260.66	$1,393.17
Median	109.61	5.17	$1,145.42	$1,107.07
Maximum	178.93	9.59	$2,054.80	$2,810.70
Minimum	88.78	2.67	$905.66	$894.61
Standard Deviation	24.76	1.61	$299.91	$542.41
Skewness	0.82	0.58	1.16	1.11
Kurtosis	2.48	2.67	3.28	2.96

Notes: Values rounded to two decimal places. Sample period: employment and unemployment 1990M01 – 2016M08. Sample period: real retail sales and real total wages 1990Q1 – 2016Q1.

All four indicator series are positively skewed (Table 2). Real total wages, real retail sales, and employment have overall upward trends, while unemployment has a downward trend. All four series exhibit cyclical patterns caused by shocks to the regional economy. These shocks cause rapid short term changes in the indicator series. The steady trends of the indicators are punctuated with small periods of high growth, resulting in positive skewness in each series.

Table 3 reports the estimated values of the coefficients for the common state, the lags of the autoregressive error term equations, and autoregressive lags of the index. The coefficients of the common state exhibit the hypothesized signs and are all statistically significant at the 1-percent level. The common state enters the employment measurement equation contemporaneously and with lags of one and two months. The common state enters the measurement equations for unemployment and real total wages contemporaneously, only. The common state enters the real retail measurement equations contemporaneously and with a one-period lag.

One measure of smoothness of the coincident index is the sum of the autoregressive coefficients of the index itself. Shocks are more persistent and the cycle is smoother when the sum is closer to one, while remaining less than one (Phillips, 2005). The index estimation includes one first-order autoregressive term with a value of approximately 0.823. The autoregressive term of the index is statistically significant at the 1-percent level.

Table 3: Estimated Coefficients

Estimated coefficients of the common state C_t				
Measurement Equation	Variable	Coefficient	Asymptotic std. error	t-statistic
Employment	C_t	0.552	0.063	8.700***
	C_{t-1}	-0.516	0.084	-6.092***
	C_{t-2}	0.359	0.059	6.039***
Unemployment Rate	C_t	-0.315	0.046	-6.805***
Real Retail Sales	C_t	0.112	0.023	4.832***
	C_{t-1}	-0.074	0.022	-3.273***
Real Total Wages	C_t	0.058	0.006	8.700***
Estimated Coefficients for lags in the autoregressive equations for the error terms				
Measurement Equation	Lag	Coefficient	Asymptotic std. error	t-statistic
Unemployment	-1	-0.056	0.063	-0.886
	-2	0.172	0.058	2.949***
	-3	0.221	0.062	3.536***
	-4	0.136	0.063	2.143**
Real Wages	-1	-0.653	0.156	-4.188***
	-2	0.143	0.198	0.725
	-3	0.346	0.159	2.171**
Estimated Coefficients for the autoregressive equation for the common factor				
Measurement Equation	Lag	Coefficient	Asymptotic std. error	t-statistic
Lag	-1	0.823	0.044	18.582***

Notes: Sample period: employment and unemployment 1990M01 – 2016M08. Sample period: real retail sales and real total wages 1990Q1 – 2016Q1.

The results of the diagnostics test on the one-step ahead prediction errors are shown in Table 4. Although both the unemployment and real wages series have statistically significant autoregressive coefficients, as shown in Table 3, the results of the diagnostics test generally indicate that the error terms of the component series are mutually uncorrelated at all leads and lags. One of the F-statistics is statistically significant at the 5-percent level and none of the other 31 coefficients are statistically significant. These results verify that idiosyncratic components of the indicators are modeled correctly and confirm the assumption that the co-movements of the component series stem from a single underlying variable.

Table 4: F-Statistics for 6-Lag Specification Test

Dependent Variables	eEmployment	eUnemployment	eRetail	eWages
eEmployment	0.581	1.174	0.416	0.314
eUnemployment	0.882	0.342	0.181	0.364
eRetail	1.352	1.507	1.328	0.564
eWages	1.679	0.880	0.717	0.810
Employment	0.507	1.637	0.463	0.171
Unemployment	1.083	0.629	0.276	0.340
Real Retail Sales	1.052	1.485	1.350	0.547
Real Total Wages	0.649	2.237**	0.902	0.598

Notes: Dependent Variable is One-Step Ahead forecast error. *p<0.10; **p<0.05; ***p<0.01. Ho: Coefficients are jointly zero. Failure to reject the null hypothesis indicates that the idiosyncratic components of indicator series are uncorrelated and implies that the presence of only one single underlying factor is a reasonable assumption. Sample period: employment and unemployment 1990M01 – 2016M08. Sample period: real retail sales and real total wages 1990Q1 – 2016Q1.

Table 5 reports the cumulative dynamic multipliers and the estimated weights for each of the indicators. The multipliers are the average growth rate of each of the indicator series and the weights are the share that each average growth rate contributes to the common co-movement growth rate, ΔC (Murphy, 2005). Employment and real wages have the greatest weights, 53.24% and 20.64% respectively. Unemployment has a weight of 13.65% and real retail sales has the smallest weight of 12.46%.

Table 5: *Cumulative Dynamic Multipliers*

Indicator	Multiplier	Share*
Employment	1.128	53.243
Unemployment	-0.289	13.651
Real Retail Sales	0.264	12.460
Real Total Wages	0.437	20.644

Notes: Values rounded to two decimal places. Sample period: employment and unemployment 1990M01 – 2016M08. Sample period: real retail sales and real total wages 1990Q1 – 2016Q1.

The average growth rate of the computed index is approximately 0.24% and has been adjusted to match the 0.21% average growth rate of Midland-Odessa annual real total personal income for the 1990 to 2014 sample period. This adjustment is made because the methodology produces a stationary index which shows changes in the business cycle but not the trends and volatility of the region (Phillips and Cañas, 2008).

Figure 1 plots the re-trended index of economic activity for the combined Midland-Odessa metropolitan economy. Although the data used to estimate the BCI begin in January or Q1 1990, the estimated BCI begins in January 1991 because employment and real retail sales include lags of the common state, C_t. This first available BCI value is used as the base period. The graph highlights six recessionary periods. Recessions for Midland-Odessa are defined as periods of at least a 0.5% decline in the coincident index with at least three months between the peak and trough (Crone, 2006). Three of the Petroplex downturns coincide with national recessions, but with later start dates (peaks) than those of the macroeconomic downturns.

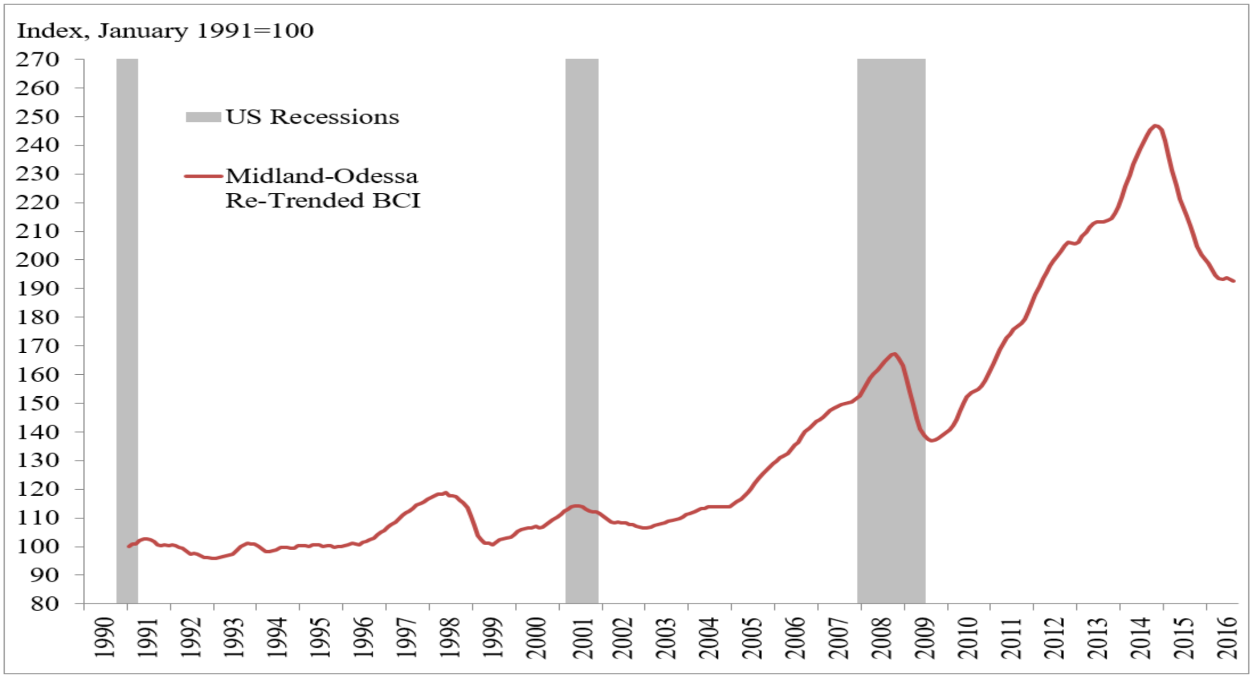

Figure 1: Petroplex Re-Trended BCI

The first local recession that is independent of a national contraction occurred between October 1993 and March 1994. The second independent contraction occurred between May 1998 and June 1999. The third independent recession begins in October 2014 and, because the index is still in decline for this most recent estimation period, a trough is not yet established for it.

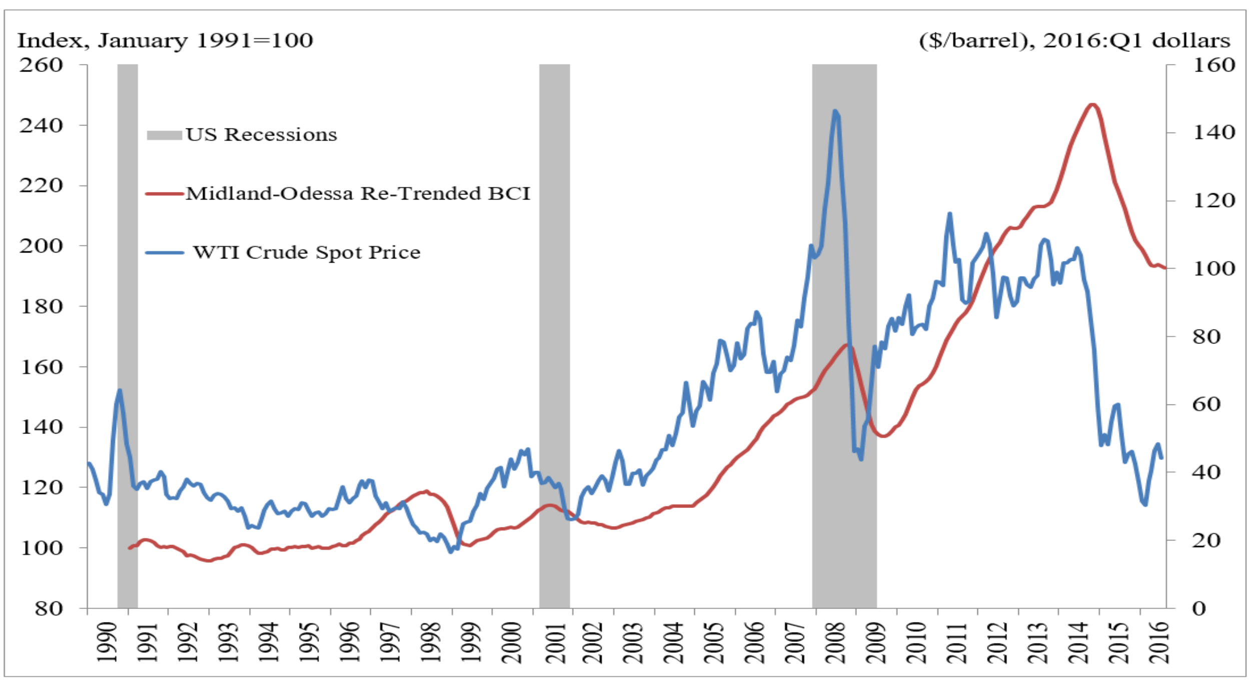

Figure 2: Petroplex Re-Trended BCI and Monthly WTI Oil Price

Figure 2 shows that all three of the Petroplex local recessions are associated with sharp declines in oil prices. Prices declined by 34% between June 1992 and March 1994, by 56% between December 2006 and December 2008, and by 59% between June of 2014 and July 2016.

Notable expansionary periods in the Permian Basin economy are also closely tied to increases in oil prices. The correlation coefficient between the contemporaneous lags of the re-trended BCI and the West Texas Intermediate oil price series during the sample period is approximately 0.668. When oil prices increased by 40% between July 1995 and December 1996, the coincident index increased by 13% between December 1996 and May 1998. Oil prices more than doubled between March 1999 and January 2001 and the index increased by 14% between June 1999 and May 2001. When oil prices more than doubled between late 2003 and mid-2006, the BCI increased by 47% between November 2004 and October 2008. Oil prices also doubled between early 2007 and mid-2008. That development likely contributed to the delayed materialization of the 2008 to 2009 national recession in Midland-Odessa.

Figure 3 shows both the index estimated in this study as well as the Midland-Odessa Regional Economic index. The latter index is published monthly by the Midland Development Corporation (MDC) and is estimated by Ingham Economic Reporting (MDC, 2016). The MDC index tracks the business cycles of the combined Midland-Odessa metropolitan area using component series that include taxable retail sales, spending on automobiles, hotel/motel tax receipts, airline passenger volumes, value of all building permits, housing sales dollar volumes, average home sales prices, unemployment, and employment (Ingham, 2013). The methodology behind the estimation of the MDC index is not disclosed, but one observable difference between its estimation and the index estimated in this study is the greater number of indicators used in the estimation of the MDC index. As seen in Figure 3, the two indexes follow very similar patterns until November 2010 when the index estimated in this study begin to exhibit higher levels of growth. In general, the movements in the two indexes are closely correlated, but the Petroplex BCI tends to mark peaks and troughs earlier than the MDC series. The MDC appears to track business cycles as more of a lagging index relative to the coincident BCI developed in this study.

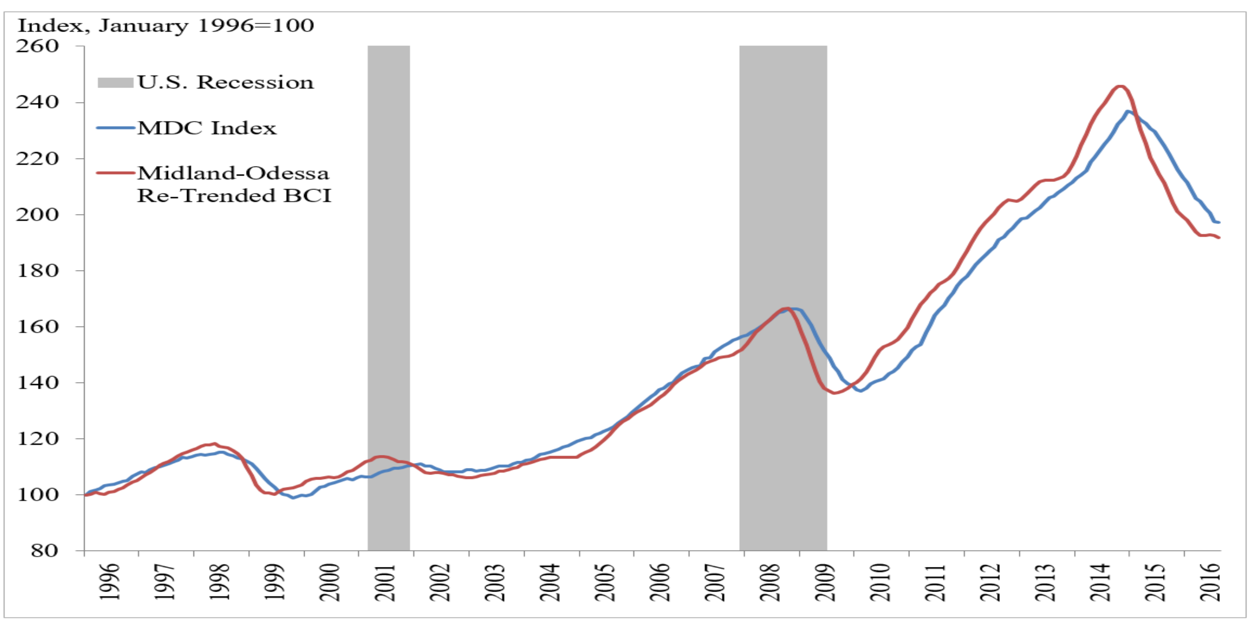

Figure 3: Petroplex BCI and MDC BCI

The Midland-Odessa Petroplex BCI offers a new tool for understanding the state of the regional economy. The timeliness and availability of the indicator series used to estimate the index allows for a more current estimation of economic conditions. It is clear that the dynamics of this economy often deviate from those of the national economy. The Petroplex BCI provides a broad-based means for better tracking business conditions in this unique metroplitan economy.

Conclusion

A dynamic single-factor modeling approach is used to estimate a coincident index for the Midland-Odessa Petroplex economy (Stock and Watson, 1991; Clayton-Matthews, 2005). The methodology assumes that the co-movements of key economic indicators have a single underlying, unobservable factor. Through an econometric approach, this factor is extracted from indicator variables and used to calculate an index that represents current economic conditions. The model also utilizes the Kalman filter smoothing approach, a recursive process that estimates mean square error estimates, facilitates the use of mixed-frequency data, and results in a smother index with less pronounced recessions and expansions. Indicator series used in this study are: employment, unemployment, inflation adjusted retail sales, and real total compensation. The data used in this study cover the period from January 1990 through August 2016.

The calculated index for Midland-Odessa is generally smooth and its movements are consistent with historical economic conditions of the region. Three of the recessionary periods in Midland-Odessa are associated with national economic contractions. Two additional recessions for this metropolitan economy follow the movement of the West Texas Intermediate crude oil price. Given that the petroleum industry is a well-known driver of the Midland-Odessa economy, the strong correlation between the coincident index and oil prices is as hypothesized.

The metropolitan business cycle index for Midland-Odessa is designed to reliably reflect current economic conditions. The approach employed is one that has been applied to other metropolitan economies in Texas (Phillips and Cañas, 2008). The new index thus provides an additional tool for monitoring Midland-Odessa economic conditions that is directly comparable to the BCI utilized for the other economic regions in Texas and has relatively limited data requirements.

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