www.kspjournals.org

Volume 4 March 2017 Issue 1

Metropolitan Business Cycle Analysis for Lubbock

By Thomas M. FULLERTO[N](#page-0-0) a^{\dagger} & Macie Z. SUBIA b

Abstract. This study develops a business cycle index (BCI) for Lubbock Metropolitan Statistical Area (MSA). The Stock & Watson [\(1989;](#page-19-0) [1991;](#page-19-1) [1993\)](#page-19-2) methodology is used to develop the BCI and assumes that the co-movements of key economic indicators have a single underlying, unobservable factor. This factor is extracted from the indicators and used to calculate an index that represents economic conditions through an econometric approach. The model uses the Kalman filter smoothing approach which smooths across variables and over time. This results in an index that is smoother with less pronounced expansions and recessions. Indicator series used for the study are: establishment employment, unemployment, real retail sales and real wages that begin in 1990 and include complete data through the end of 2015. Results indicate that the Lubbock business cycle has peaks and troughs that occur later than those for the national economy.

Keywords. Regional Economics; Business Cycles; Economic Indicators. **JEL.** R15, E32.

1. Cities and Technology: From Industrial to AI Era

The economic performance of Lubbock is generally difficult to assess. Although some monthly labor market and real estate data exist, there is no overall gauge of current economic activity [\(LEDA, 2009\)](#page-19-3). One means for The economic performance of Lubbock is generally difficult to assess.
Although some monthly labor market and real estate data exist, there is no overall gauge of current economic activity (LEDA, 2009). One means for doing designed using a set of economic indicators that define the state of an economy over time [\(Cañas, Coronado, & Lopez, 2005\)](#page-19-4). While BCIs are useful tools, relatively few exist for metropolitan economies in the United States.

The objective of this study is to develop a BCI for Lubbock. To achieve that goal, the Stock & Watson [\(1998;](#page-19-5) [1999\)](#page-19-6) methodology is used to create the index. Indicators utilized for this purpose include establishment employment, the unemployment rate, real wages, and real retail sales. The empirical method extracts from each series information relevant to the current state of the Lubbock economy and combines this information into an index that reflect metropolitan business cycle conditions [\(Cañas, Gilmer, & Phillips, 2003\)](#page-19-7).

Remaining sections of the study are as follows. A brief overview of prior research on regional business cycle indices is provided in the next section. Data and methodology are reviewed next. Empirical results are then discussed. The final section includes a summary and closing statements.

^aDepartment of Economics &Finance, University of Texas at El Paso, El Paso, TX 79968-0543, USA.

 $3.915 - 747 - 7747$

 \blacktriangleright tomf@utep.edu

 b Department of Economics &Finance, University of Texas at El Paso, El Paso, TX 79968-0543, USA.

³.915-227-9935

 $\mathbf{\times}$. mzsubia@outlook.com

2. Literature Review

The need to measure overall economic activity, and the lack of consensus on the appropriate method to do so, has led to a great deal of research on BCIs. Beginning in 1930, the National Bureau of Economic Research (NBER) started publishing empirical business cycle studies (Burns & Mitchell, 1946). That approach sought to explain business cycles using two elements. First are co-movements among individual economic variables, which allow the creation of composite leading, coincident, and lagging indexes (Diebold & [Rudebusch, 1996\)](#page-19-8). Second is the division of business cycles into separate phases related to expansions and contractions of the economy. Initial NBER efforts included 487 economic variables in an attempt to identify turning points and determine whether variables lead, coincide, or lag changes in overall business conditions [\(Cañas, Gilmer &](#page-19-7) Phillips, [2003\)](#page-19-7). Reliable series were eventually grouped into composite indexes of leading, coincident, and lagging economic indicators [\(Phillips, 1998;](#page-19-9) [1999\)](#page-19-10). From 1960 through 1995, the U.S. Department of Commerce housed the composite indexes [\(Phillips, 2005\)](#page-19-11).

Since 1995, the Conference Board (CB) has produced the coincident indexes for the U.S. economy. The index combines the movements of employees on nonagricultural payrolls, personal income less transfer payments, an index of industrial production, and manufacturing and trade sales [\(CB, 2012\)](#page-19-12). Thecoincident index is calculated by averaging the four economic data series for smoothness, and the volatility of each indicator is then equalized using a predetermined standardized factor, which the CB updates once a year [\(CB, 2012\)](#page-19-12).

As an alternative approach, Stock & Watson [\(1989;](#page-19-0) [1991;](#page-19-1) [1993\)](#page-19-2) develop a dynamic single-index factor model using a Kalman filter. Stock & Watson [\(1989\)](#page-19-0) construct the coincident index with the same indicators as the CB model but use a different employment variable [\(Phillips, 2005\)](#page-19-11). Stock & Watson statistically estimate the weights of the component series that best identifies a single, timedependent, underlying factor (Stock & [Watson, 1989\)](#page-19-0). The process incorporates co-movements in the components and attempts to identify the underlying state of the economy (Cañas, Gilmer $\&$ Phillips, 2003). The model uses the Kalman filter smoothing approach which smooths across variables and over time. This results in an index which is smoother because it turns down less often during expansions and increases less often during recessions (Phillips & [Cañas, 2004\)](#page-19-13).

Clayton-Matthews $\&$ Stock [\(1998;](#page-19-14) [1999\)](#page-19-15) apply this methodology to the Massachusetts economy to estimate coincident and leading indexes. The coincident indicators must exhibit comovement with regional economic activity, high frequency, timely availability, historical availability, reliability, low noise, and robustness to revisions. The variables used for the Massachusetts coincident indicator model are measures of employment, the income tax base, the sales tax base, and the unemployment rate [\(Clayton-Matthews &](#page-19-14) Stock, 1998; [1999\)](#page-19-14).

Phillips [\(2005\)](#page-19-11) estimates a Texas coincident index using that methodology, also.

Variables used include nonfarm employment, quarterly Texas Real Gross State Product (RGSP), and the Texas unemployment rate. One-step ahead forecast errors, described in Clayton-Mathews $\&$ Stock [\(1998;](#page-19-14) [1999\)](#page-19-14), are tested to determine whether the white noise components of the error terms are uncorrelated with past values of itself, the forecast errors of other indicators, and past changes in the indicators. Furthermore, the Neftci [\(1982\)](#page-19-16) test confirms that the new Texas coincident index has fewer false signals and improved timing for predicting recessions than the Phillips [\(1988\)](#page-19-9) index. The cyclical behavior of the new index is also found to be correlated with the employment and RGSP indicators.

Cañas, Gilmer, & Phillips [\(2003\)](#page-19-7) develop a coincident index for the Houston metropolitan economy using the Stock $\&$ Watson model. The coincident index developed uses the indicators of established employment, unemployment rate, real wages, and real retail sales. Additionally, the average growth rate of personal income is used to re-trend the series. The coincident index is correlated with

historical U.S. economic recessions and expansions. Cañas, Gilmer, & Phillips [\(2003\)](#page-19-7) use the same methodology and indicators to create a coincident index for the El Paso metropolitan economy. The coincident index for El Paso follow the U.S. industrial production manufacturing index along with Ciudad Juarez maquiladora employment due to the high international involvement with Mexico.

Phillips & Cañas [\(2008\)](#page-19-17) use the dynamic single-factor approach to measure business cycles in four Texas border economies and Mexico. Seasonally adjusted changes in non-farm employment, the unemployment rate, real wages, and retail sales are used to determine coincident indexes for El Paso, Laredo, Brownsville / Harlingen (Brownsville), and McAllen/Edinburg/Mission (McAllen). Correlation, spectral, and cluster analysis are used to study economic integration between border cities, the US, Texas, and Mexican economies. The correlation and spectral analysis allow to test for breaks in the cyclical relationships between the border economies and broader economies after 1994, the year the North American Free Trade Agreement (NAFTA) was enacted. Results obtained indicate that business cycles in Brownsville, McAllen, and Laredo have become increasingly correlated with the business cycle in Mexico subsequent to 1994. In contrast, the business cycle of El Paso has become comparably more aligned with the business cycles of Texas and the US.

The Stock & Watson methodology has been applied to data for a variety regional economies to create BCIs. The BCIs estimated using this methodology have been shown to provide informative and accurate measures of the overall states of the respective economies analyzed. Accordingly, the Stock & Watson methodology is used to estimate a BCI for the Lubbock metropolitan economy. The four broad regional indicators used to estimate the BCI are establishment employment, the unemployment rate, real wages, and real retail sales.

3. Theoretical Model and Data

Stock & Watson [\(1989;](#page-19-0) [1991;](#page-19-1) [1993\)](#page-19-2) develop and apply the dynamic single factor, multiple indicator model at the national level. This study utilizes this basic model to estimate a BCI for Lubbock. The fundamental structure of the dynamic single factor model is:

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

$$
D(L)\mu_t = \varepsilon_t \tag{2}
$$

$$
\phi(L)\Delta C_t = \delta + \eta_t \tag{3}
$$

where $Y_t = \Delta X_t$ are the stationary first differences of natural logs of the coincident component series and C_t represents the log of the unobserved state of the economy. *L* represents the lag operator. The lag polynomials $\phi(L)$ and $D(L)$ are assumed to have finite orders p and k, respectively. The disturbances ε_t and η_t are assumed to be serially uncorrelated and uncorrelated with each other at all leads and lags. The lag polynomial matrix $D(L)$ is assumed diagonal, implying that the μ_t are contemporaneously and serially uncorrelated with each other.

Seasonally adjusted changes in non-farm employment, the unemployment rate, real total wages, and real retail sales are used to define a coincident index for Lubbock. The series are converted to first differences of natural logs (except the unemployment rate which is just differenced) and normalized by subtracting the respective mean differences and dividing by the respective standard deviation of those differences. This results in $\beta = 0$ in Equation (1) and $\delta = 0$ in Equation (3). The scale of the $\gamma(L)$ coefficients is fixed by setting the variance of η to one and the timing of the coincident index is fixed by setting $\gamma_1(L) = 0$ for employment in Equation (1). An assumption for all other indicators is that $\gamma_i(L) = 0$ for all lags greater than 2. This allows the component to have up to a two-month, or twoquarter, lag with the business cycle index.

Equation (3) defines the dynamics of the underlying state of the economy, while Equation (1) shows how each of the component series is associated to this underlying growth process. ΔC_t is the common comovement in the growth of the indicators, Y. The idiosyncratic components of each of the time series are modeled in Equation (2). The idiosyncratic components, μ , are stationary, mean zero, autoregressive stochastic processes [\(Clayton-Matthews &](#page-19-14) Stock, 1998; [1999\)](#page-19-14). Growth in the state of the economy is modeled as a stationary autoregressive process. Phillips & Cañas [\(2008\)](#page-19-17) indicates that if the component series of Y_t move together with the metropolitan economy, then the common movement C_t can be interpreted as the current state of that economy, also known as the coincident index.

Maximum likelihood estimates of the parameters of Equations (1) - (3) and estimation of the filtered state are attained by representing Equations (1) - (3) in state form and using a Kalman filter [\(Clayton-Matthews & Stock, 1998; 1999\)](#page-19-14). This formulation has two parts, the state equation and the measurement equation. The state equation describes the evolution of the unobserved state vector, which consists of ΔC_t , μ_t , and their lags. The measurement equation relates the observed variables to the elements of the state vector (Stock & [Watson, 1991\)](#page-19-1).

The state equation is obtained 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 at this point by the identity $C_{t-1} = \Delta C_{t-1}$ + C_{t-2} [\(Stock & Watson, 1991\)](#page-19-1). The transition equation for the state is thus given by:

$$
\begin{bmatrix} C_{t-1}^{*} \\ \mu^{*} \\ C_{t} \end{bmatrix} = \begin{bmatrix} \phi^{*} & 0 & 0 \\ 0 & D^{*} & 0 \\ Z_{c} & 0 & 1 \end{bmatrix} \begin{bmatrix} C_{t-1}^{*} \\ \mu_{t-1}^{*} \\ C_{t-2} \end{bmatrix} + \begin{bmatrix} Z_{c}' & 0 \\ 0 & Z_{\mu}' \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \eta_{t} \\ \varepsilon_{t} \end{bmatrix}
$$
 (4)

where:

$$
C_t^* = \begin{bmatrix} \Delta C_t & \Delta C_{t-1} & \dots & \Delta C_{t-p+1} \end{bmatrix}'
$$

\n
$$
\mu_t^* = \begin{bmatrix} \mu_t & \mu_{t-1} & \dots & \mu_{t-k+1} \end{bmatrix}'
$$

\n
$$
\phi^* = \begin{bmatrix} \phi_1 & \dots & \phi_{p-1} & \phi_p \\ l_{p-1} & 0_{(p-1)\times 1} \end{bmatrix}
$$

\n
$$
D^* = \begin{bmatrix} D_1 & \dots & D_{k-1} & D_k \\ l_{n(k-1)} & 0_{n(k-1)\times n} \end{bmatrix}
$$

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

\n
$$
Z_\mu = \begin{bmatrix} l_n & 0_{n \times n(k-1)} \end{bmatrix}
$$

and where I_n denotes the $n \times n$ identity matrix, $0_{n \times k}$ denotes and $n \times k$ matrix of zeros, and $D_i = diag(d_{1i}, ..., d_{ni})$, where $d_j(L) = 1 - \sum_{i=1}^{k} d_{ji} L^i$.

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

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

Asterisks are used for notational compactness to indicate that a vector of variables or a matrix of variables is actually being employed. Equations (4) and (5) become less unwieldy by doing so (Stock & [Watson, 1989;](#page-19-0) [1991\)](#page-19-1).

Equations (4) and (5) can be rewritten in the standard form:

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

(7)

$$
Y_t = \beta + Z\alpha_t + \xi_t
$$

where:

$$
\alpha_t = (C_t^{*'} \mu_t^{*'} C_{t-1})'
$$

$$
\zeta_t = (\eta_t \varepsilon_t)
$$

and where the matrices T_t , R, and Z respectively denote the transition matrix in Equation (5), the selection matrix in Equation (5), and the selection matrix in equation (6), and $\mu_{\alpha} = (\delta 0_{1x(p+nk)})'$. The covariance matrix of ζ_t is $E \zeta_t \zeta_t' = \sum$. For generality, a measurement error term ξ_t , assumed uncorrelated with ζ_t , has been added to the measurement Equation (8), and the transition matrix T_t is allowed to vary over time.

The Kalman filter is applied to this state representation of the model. Let $\alpha_{t|\tau}$ denote the estimate of α_t based on $(y_1, ..., y_\tau)$, let $E[\xi_t \xi_t] = H, E[\zeta_t \zeta_t] = \sum$, 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:

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

$$
P_{t|t-1} = T_t P_{t-1|t-1} T_t' + R \Sigma R'
$$
\n(9)

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

$$
\alpha_{t|t} = \alpha_{t|t-1} + P_{t|t-1} Z' F_t^{-1} \nu_t
$$
\n(10)

$$
P_{t|t} = P_{t|t-1} - P_{t|t-1} Z' F_t^{-1} Z P_{t|t-1}
$$
\n(11)

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

Clayton-Mathews & Stock [\(1998;](#page-19-14) [1999\)](#page-19-15) describes the three outcomes of this procedure: $\Delta C_{t|t-1}$, which are the prediction estimates; $\Delta C_{t|t}$, which are the filtered estimates; and ΔC_{t} , which are the smoothed estimates. In the prediction estimates, the state of each period is estimated with information available through the prior period. The predication estimates are used to form one-step ahead prediction errors, $\hat{\epsilon}_{t|t-1} = \Delta x_t - \Delta x_{t|t-1}$, which are used to calculate the likelihood based on the initial parameter estimates. These predication 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 filtered estimates use information available through the current period. The smoothed estimates use the entire set of information in the sample to estimate the state in each period [\(Clayton-Matthews & Stock, 1998; 1999\)](#page-19-14). The two estimates are commonly referred to as "Kalman filter" and "Kalman smoother," respectively. The analysis uses the Kalman smoother with weights that rapidly approach zero as they move away from the current period. As the data approach the end of the sample, the estimates go to $\Delta C_{t|t}$ [\(Clayton-Matthews & Stock, 1998; 1999\)](#page-19-14).

From Equation (3), the Kalman filter models each of the component series as left-hand side variables with the (unobserved) coincident index on the right hand side. From the given structure, quarterly variables are modeled as functions of current and past values of the monthly underlying series. This allows quarterly data to enter the equations with monthly data as follows:

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

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

The methodology employed produces indexes which are designed to be stationary and have unit variances. In order to make the index reflective of the distinctive movements and the volatility in the region, two adjustments are made. 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 in the index is set equal to the average growth in real metropolitan personal income over the course of the sample period (Phillips $& Cañas, 2008$).

The data for this study begin in 1990 because the Bureau of Labor Statistics (BLS) have only reconstructed data series using the 2007 North American Industry Classification System (NAICS) back to 1990. Combining the Standard Industrial Classification (SIC) system data with NAICS data can produce biased estimates (Tebaldi and Kelly, 2012). Non-farm seasonally adjusted payroll employment monthly data series are available from 01:1990 to 07:2016 from the Federal Reserve Bank of Dallas (FRBD). Unadjusted non-farm employment data series are retrieved by FRBD from the Quarterly Census of Employment and Wages (QCEW), published by BLS in collaboration with the Texas Workforce Commission. The QCEW data account for 98 percent of all county, metropolitan, state, and national jobs in the USA. Berger & Phillips [\(1993;](#page-19-18) [1994\)](#page-19-19) describe a twostep seasonal adjustment process that estimates and applies two separate seasonal adjustment factors for the two separate parts of the data. Early benchmarking and two-step seasonal adjustments are done by FRBD.

Another monthly indicator is the unemployment rate available from 01:1990 to 07:2016 from FRBD. The unemployment rate data are retrieved from the BLS and seasonally adjusted by the FRBD using the X-12 procedure. Those data are released at the same time as non-farm employment figures each month.

The Lubbock BCI also uses quarterly retail sales which are available from Q1:1990 to Q4:2015 and compiled by the Texas Comptroller of Public Accounts. To avoid bias in the retail sales indicator, data prior to 2002 are converted into NAICS using the 2002 NAICS to 1987 SIC concordance provided by the U.S. Census Bureau [\(USCB, 2002\)](#page-19-20). The retail sales data series are then seasonally adjusted using the X-12 procedure and adjusted for inflation using Q4:2015 as the base period. Total wage data are available from Q1:1990 to Q4:2015 and obtained from the Texas Workforce Commission. Total wage data are seasonally adjusted with the X-12 procedure and then adjusted for inflation using Q4:2015 as the base period.

4. Empirical Analysis

Dynamic Single-Factor Model (DSFM) software is used to estimate the BCI for the Lubbock MSA economy. The structure of the model, estimation, and transformation from the estimated state to the economic index are developed using Stock & Watson methodology [\(Clayton-Matthews, 2005\)](#page-19-15). Four seasonally adjusted indicators are used to create the coincident index for Lubbock: establishment employment, the unemployment rate, real retail sales, and real total wages. Table 1 lists the variables and their descriptions.

Table 2 provides summary statistics for each indicator. The employment indicator for Lubbock MSA over the course of the sample period reaches a maximum of about 142 thousand and follows a gently upward-sloping trend. The unemployment indicator exhibits a more cyclical movement with a minimum of 2.7 percent and a maximum of 6.7 percent throughout the sample period. The retail sales indicator experiences a slight dip in 2002 due to the conversion of SIC to NAICS codes for the time series data from 1990 to 2001. Real retail sales have a skewness of 0.401566 and kurtosis of 2.405778. Real total wages increase steadily over the course of the sample period and display a skewness of 0.02629 and a kurtosis of 2.163425.

Table 1. *Variables, Definitions, and Units of Measure*

Notes: * Wages represent total compensation paid during the calendar quarter, regardless of when services were performed. Included in wages are wages, salaries, pay for vacation and other paid leave, bonuses, stock options, tips, the cash value of meals and lodging.

Sample period: Employment and Unemployment 01:1990 – 07:2016. Real Retail Sales and Real Total Wages Q1:1990 – Q4:2015.

The coefficient estimates for the BCI model are reported in Table 3. In the table, the b prefix represents the γ parameters from Equation (1). The t-statistics for employment, unemployment rate, real retail sales, and real wages are strongly significant and the coefficients exhibit the expected signs.

The coinindxar estimates in Table 3, refer to the autoregressive coefficients $(\phi(L))$ of ΔC_t as described in Equation (3). Autoregressive coefficients of the coincident index itself are included in order to further reduce month to month noisiness. Fifth-order autoregression coefficients are included into the coincident index and are statistically significant. One measure of smoothness is the sum of the autoregressive coefficients of the coincident index. The closer the sum of the autoregressive coefficients is to one, while remaining less than one, the smoother the BCI [\(Phillips, 2005\)](#page-19-11). The autoregressive coefficients of the BCI, sum to 0.799593.

 In Table 3, the ar prefix refers to the autoregressive parameters from Equation (2) and the s parameters measure the variance of the error terms in Equation (2). The autoregressive parameters are determined by a univariate equation for each transformed series and statistically significant autoregressive terms are included in the estimation of the BCI. The employment, unemployment rate, and retail sales are employed with first-order autoregression. Second-order autoregression coefficients are incorporated into the model for the wage indicator. The autoregressive coefficients for each of the indicators are statistically significant. The specification search that led to the estimated autoregressive structures of the idiosyncratic portions of the indicators in Equation (2) were aided by the white noise specification test.

Sample period: Employment and Unemployment 01:1990 – 07:2016. Real Retail Sales and Real Total Wages $Q1:1990 - Q4:2015$.

Note: *p<0.10; **p<0.05; ***p<0.01.

Table 4 reports the results of the whiteness test performed on the one-step-ahead errors from Equation (2). The test assesses whether the noise components in Equation (2) are predictable. Clayton-Matthews & Stock [\(1998; 1999\)](#page-19-14) use the test to check the assumption of a single latent factor by verifying that one-step ahead forecast errors $\varepsilon_{t|t-1}$ are uncorrelated with previous values of itself, the forecast errors of the other indicators, and previous changes in the indicators. The test is implemented using a series of regressions. For each regression, the dependent variable is one of the one-step ahead forecast errors of the component series, and the independent variables consist of a constant and six lags each of the forecast errors and the indicators. An F-test is then performed on the joint significance of each regression. The p-values correspond to the F-test of the null hypothesis that the coefficients, other than the constant, are all zero (Clayton-Matthews $\&$ Stock, [1998; 1999\)](#page-19-14).

If the single index model has the proper specification, the coefficients on the lags should jointly be insignificantly different from zero. Only one out of the thirty-two F-statistics is significant at the 5% level. Generally, the hypothesis that the coefficients on the six lags are jointly indistinguishable from zero cannot be rejected, which supports the assumption of a single common factor.

| | | Dependent Variables | | |
|------------|----------|---------------------|----------|----------|
| | eEMP | eUR. | eRRS | eWSD |
| eEMP | 0.534485 | 2.17698** | 1.48439 | 0.834579 |
| eUR | 0.479343 | 0.499904 | 0.490425 | 0.155985 |
| eRRS | 1.26506 | 0.591134 | 0.513299 | 0.988615 |
| eWSD | 0.426109 | 0.566386 | 0.680802 | 1.56898 |
| EMP | 0.49195 | 1.68487 | 1.70699 | 0.821974 |
| UR | 0.405473 | 0.35392 | 0.457348 | 0.236261 |
| RRS | 0.891985 | 0.534071 | 0.259539 | 1.04359 |
| WSD | 0.52431 | 0.525605 | 0.90335 | 0.831168 |

Table 4. F-Statistics for 6-lag Specification White Noise Test with One-Step Ahead Forecast Error used as the Dependent Variable

Sample period: Employment and Unemployment 01:1990 – 07:2016. Real Retail Sales and Real Total Wages $Q1:1990 - Q4:2015$

Note: *p<0.10; **p<0.05; ***p<0.01. Ho: Coefficients are jointly zero. Failure to reject Ho supports the existence of a single common factor.

The cumulative dynamic multipliers are the average growth rates 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 [\(Murphy, 2005\)](#page-19-21). Table 5

lists the cumulative dynamic multipliers and the component shares. The dynamic cumulative multipliers indicate the response of the estimated state to a unit pulse in each indicator. Each dynamic cumulative multiplier gives the relative importance of each indicator in forming the estimated state. The cumulative weighted multipliers suggest the following weighting scheme for the indicators: employment, 1.45201; unemployment rate, -0.789402; real retail sales, 0.296703; real wages, 0.551994. The employment indicator for Lubbock gets the greatest weight followed by the unemployment rate. Changes in the employment represent 46.99% of the movement in the index, while changes in the unemployment rate get a weight of 25.55%. The larger weight assigned to employment is a helpful result due to the reliability and timeliness of the employment series. It should reduce the impacts of revisions caused by the later incorporation of the quarterly data values for retail sales and wages (Phillips $\&$ [Cañas, 2008\)](#page-19-17).

Table 5. Lubbock BCI Cumulative Dynamic Multipliers

| | Variable | Multiplier | Share | |
|--|-------------------|-------------|---------|--|
| | Employment | 1.45201 | 46.9889 | |
| | Unemployment Rate | -0.789402 | 25.5461 | |
| | Real Retail Sales | 0.296703 | 9.60171 | |
| | Real Wages | 0.551994 | 17.8633 | |
| | . | | . | |

Sample period: Employment and Unemployment 01:1990 – 07:2016. Real Retail Sales and Real Total Wages $Q1:1990 - Q4:2015$

Figure 1 plots the computed index of coincident economic activity in the Lubbock MSA. The index maps cyclical swings in the economy, but not long-term trends in economic growth [\(Cañas, Gilmer, & Phillips, 2003\)](#page-19-7). The BCI produced by the methodology employed is designed to be stationary and have a unit variance. Adjustments are made in order to make the index reflective of the distinctive movements and volatility in the region. The coincident index is retrended and scaled to historical growth in real personal income published by the Bureau of Economic Analysis (BEA). Personal income offers a broad measure of the local economy, but cannot be used in the coincident index because of annual periodicity. This series is used to set the BCI long-run trend [\(Phillips &](#page-19-13) Hamden, [2004\)](#page-19-13). Shading in Figure 1 indicates the beginning and end of recessions for the U.S. based on the dates from the NBER.

As shown in Figure 1, the last three national recessions have been accompanied by regional downturns in Lubbock. That is not surprising, but the BCI indicates that recoveries from all three downturns took longer to materialize in Lubbock than elsewhere. A potential reason behind that is the prevalence of manufacturing in Lubbock and the multiple stresses and structural changes affecting those sectors

during the rapid globalization era of the world economy [\(Cañas, Gilmer, &](#page-19-7) [Phillips, 2003\)](#page-19-7). Several other major developments affected the Lubbock economy during the sample period. Retail trade benefited from exceptional cotton crops in 1993 and 1997 as well as the ongoing consolidation of regional business activity in Lubbock [\(CLPD & LEC, 2000\)](#page-19-22). Encouragingly, the closures of the Reese Air Force Base in 1997 and a Texas Instruments Plant in 1998 did not translate into economy-wide slumps.

The BCI represents a new tool for understanding the local economic performance in Lubbock. It incorporates movements in four regional indicators: establishment employment, unemployment, real retail sales, and real wages. Given how much Lubbock economic conditions can deviate from national business cycle developments, the BCI provides a potentially helpful tool to business and policy analysts for this region of Texas.

5. Conclusion

This study employs the coincident index estimation procedure proposed by Stock & Watson [\(1989;](#page-19-0) [1991;](#page-19-1) [1993\)](#page-19-2) and software developed by Clayton-Matthews [\(2005\)](#page-19-15) to create a BCI for Lubbock. A dynamic factor model that aggregates the underlying movements of establishment employment, unemployment rate, retail sales, and wages is estimated to provide a summary measure of current economic activity. The empirical method extracts from each indicator information relevant to the current state of the Lubbock economy and combines this information into an index that reflects metropolitan business cycle conditions.

Each indicator incorporated into the BCI starts from the year 1990, including retail sales, following conversion from SIC to NAICS for the years 1990 to 2001. The parameter estimates are statistically significant for Equations (1) - (3), and form the heart of the model. The sum of the autoregressive coefficients used to calculate the coincident index is 0.799593. The closer the sum of the autoregressive coefficients is to one, while remaining less than one, the smoother the resulting BCI. The Lubbock BCI is fairly smooth. Overall movements in the Lubbock BCI follow the last three national recessions, but recovery phases for this regional economy took longer to materialize.

The Lubbock BCI of coincident activity offers a tool for understanding local economic performance by helping to identify turning points, expansions, and recessions in this region of Texas. Because it employs the same method that is used to analyze other metropolitan economies of Texas, the Lubbock BCI provides information that is comparable to what is utilized for other areas of the state. It will potentially help analysts more reliably gauge economic conditions relative to those prevailing elsewhere in Texas.

Historical Data Appendix

Table A1. *MonthlyHistorical Data*

Table A3. *Lubbock Business Cycle Index*

JEPE, 4(1), T. Fullerton, & M.Z. Subia, p.33-52.

References

Berger, F.D., & Phillips, K.R. (1993). Reassessing Texas employment growth. Federal Reserve Bank of Dallas Southwest Economy, July/August, 1-3. [\[Retrieved from\]](http://econpapers.repec.org/scripts/redir.pf?u=http%3A%2F%2Fdallasfed.org%2Fassets%2Fdocuments%2Fresearch%2Fswe%2F1993%2Fswe9304a.pdf;h=repec:fip:feddse:y:1993:i:jul:p:1-3:n:4).

Berger, F.D., & Phillips, K.R. (1994). Solving the mystery of the disappearing January blip in state employment data. Federal Reserve Bank of Dallas Economic Review, Second Quarter, 53-62. [\[Retrieved from\]](https://www.google.com.tr/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwjo-cnBtK7SAhWhKJoKHRcjAykQFggZMAA&url=https%3A%2F%2Fwww.dallasfed.org%2Fassets%2Fdocuments%2Fresearch%2Fer%2F1994%2Fer9402d.pdf&usg=AFQjCNGtvM1oQp-XH5dogEJKQU79P8p).

Burns, A., & Mitchell, W. (1946). Measuring Business Cycles. NBER, New York, NY.

- Cañas, J., Coronado, R., & Lopez, J.J. (2005). Cyclical differences emerge in border city economies. Federal Reserve Bank of Dallas Vista, 2, 1-5. [\[Retrieved from\]](http://dallasfed.org/assets/documents/research/vista/vista0502a.pdf).
- Canas, J., Gilmer, R.W., & Phillips, K. (2003a). A New Index of Coincident Economic Activity for Houston. Federal Reserve Bank of Dallas Houston Business, April, 1-3. [\[Retrieved from\]](http://www.dallasfed.org/assets/documents/research/houston/2003/hb0303.pdf).
- Cañas, J., Gilmer, R.W., & Phillips, K. (2003b). Composite Index: A New Measure of El Paso's Economy. Federal Reserve Bank of Dallas Business Frontier, 1, 1-4. [\[Retrieved from\]](http://www.dallasfed.org/assets/documents/research/busfront/bus0301.pdf).

CB, (2012). Global Business Cycle Indicators. New York, NY: The Conference Board.

- Clayton-Matthews, A. (2005). DSFM Manual. Boston, MA: University of Massachusetts.
- Clayton-Matthews, A., & Stock, J.H. (1998/1999).An application of the Stock/Watson index methodology to the Massachusetts economy, Journal of Economic and Social Measurement, 25(3-4), 183-234.
- CLPD & LEC. (2000). Lubbock Economic Indicators 1990 - 1999. Lubbock, TX: The City of Lubbock Planning Department and the Lubbock Economics Council.
- Diebold, F.X., & Rudebusch, G.D. (1996). Measuring business cycles: A modern perspective, Review of Economics and Statistics, 78(1), 67-77. doi[. 10.2307/2109848](http://dx.doi.org/10.2307/2109848)
- LEDA. (2009). Lubbock, Texas: 2009 Community Profile. Lubbock, TX: Lubbock Economic Development Alliance.

Murphy, A.P. (2005). An Economic Activity Index for Ireland: The Dynamic Single-Factor Method (No 4/RT/05). Dublin, IE: Central Bank and Financial Services Authority of Ireland. [\[Retrieved from\]](http://www.centralbank.ie/publications/documents/4RT05.pdf).

- Neftici, S.N. (1982). Optimal prediction of cyclical downturns, Journal of Economic Dynamics and Control, 4, 225-241. doi. [10.1016/0165-1889\(82\)90014-8](http://dx.doi.org/10.1016/0165-1889%2882%2990014-8)
- Phillips, K.R. (1988). New tools for analyzing the Texas economy: Indexes of coincident and leading economic indicators. Federal Reserve Bank of Dallas Economic and Financial Policy Review, July, 1- 13.
- Phillips, K.R. (1998/1999). The composite index of leading economic indicators: A comparison of approaches. Journal of Economic and Social Measurement, 25(3-4), 141-162.
- Phillips, K.R. (2005). A New Monthly Index of the Texas Business Cycle. Journal of Economic and Social Measurement, 30(4), 317-333.

Phillips, K.R., & Cañas, J. (2008). Regional business cycle integration along the US–Mexico border. Annals of Regional Science, 42(1), 153-168. doi. [10.1007/s00168-007-0124-8](http://dx.doi.org/10.1007/s00168-007-0124-8)

Phillips, K.R., & Hamden, K.T. (2004). Steady-as-she-goes? An analysis of the San Antonio business cycle. Federal Reserve Bank of Dallas Vista. Winter, 1-6. [\[Retrieved from\]](http://dallasfed.org/assets/documents/research/vista/vista0402.pdf).

Stock, J.H., & Watson, M.W. (1989). New indexes of coincident and leading economic indicators.NBER Macroeconomics Annual, 4, 351-409. [\[Retrieved from\]](http://papers.nber.org/books/blan89-1).

- Stock, J.H., & Watson, M.W. (1991). A probability model of the coincident economic indicators. Chapter 4 in Leading Economic Indicators: New Approaches and Forecasting Records, K. Lahiri & G. Moore (Eds.), Cambridge, UK: Cambridge University Press.
- Stock, J.H., & Watson, M.W. (1993). A procedure for predicting recessions with leading indicators: Econometric issues and recent experience. Chapter 2 in Business Cycles, Indicators and Forecasting, J.H. Stock & M.W. Watson (Eds.), Chicago, IL: University of Chicago Press.
- Stock, J.H., & Watson, M.W. (1998). Business Cycle Fluctuations in US Macroeconomic Time Series (No. w6528). Cambridge, MA: National Bureau of Economic Research, Inc. doi[. 10.3386/w6528](http://dx.doi.org/10.3386/w6528)
- Stock, J.H., & Watson, M.W. (1999). Business cycle fluctuations in US macroeconomic time series, Chapter 1 in Handbook of Macroeconomics, Volume 1A, J.B. Taylor and M. Woodford (eds.), New York, NY: North-Holland.
- Tebaldi, E., & Kelly, L. (2012). Measuring Economic Conditions: An Extension of the Stock/Watson Methodology. Applied Economics Letters, 19(18), 1865-1869. doi[. 10.1080/13504851.2012.669453](http://dx.doi.org/10.1080/13504851.2012.669453)
- USCB. (2002). United States Census Bureau North American Industry Classification System Concordances, 2002 NAICS to 1987 SIC. Washington, DC: U.S. Department of Commerce.

Copyrights

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-nc/4.0).

