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This study analyzes Texas state and metropolitan economic downturn predictability. Publicly available Federal Reserve Bank of Dallas dynamic factor business cycle indices are used in the analysis. Sample data cover Texas and nine of its largest metropolitan economies from January 1991 through May 2018. Dynamic autoregressive probit downturn models are estimated using the United States yield spread plus other regional and macroeconomic variables. Predictive accuracy is analyzed using in-sample model simulations. Results indicate that narrowing yield spreads, real peso appreciation, and oil price declines are generally found to increase recession likelihoods. Varying lag structures and equation specifications indicate that the state and metropolitan economies exhibit distinct timing patterns and follow different paths and each has an individual business cycle. Good predictive properties are also documented for the equations.

Introduction

Economic recession prediction is an area of interest for public and private decision makers. For national economies, the yield spread, the difference between long-term and short-term treasury bills, is a valuable business cycle contraction forecasting tool (Estrella–Mishkin 1996, Dueker 1997). Yield spreads tend to be the only financial variable that effectively predicts recessions after one quarter (Estrella–Mishkin 1998). Research by Nyberg (2010) and Kauppi–Saikkonen (2008) show that usage of the yield spread within dynamic binary response models outperforms standard static models in predicting future downturns.

Yield spreads have also been shown to effectively predict economic recessions for state economies (Gauger–Schunk 2002, Shoesmith 2003), but there is relatively little research on this topic for metropolitan economies. That gap in the literature is somewhat puzzling. Historically, there is much more information available regarding national and regional economies than there is for urban economies (Klein 1969). Given the relative paucity of information regarding metropolitan economies, the potential predictability of business cycle downturns for these areas by models with minimal data requirements may provide a very useful tool to policymakers and business analysts.

While the latter is true, metropolitan business cycle indices (BCIs) are not widely available. This study takes advantage of previously published regional BCIs maintained and updated by the Federal Reserve Bank of Dallas. Those indices are compiled using a well-known methodology involving Kalman filtering and dynamic single-factor analysis (Stock–Watson 1991). As coincident indicators, these BCIs provide gauges of current economic conditions for each of the geographic areas monitored (FRBD 2018). Those indices are published for the five largest urban economies in Texas, the four largest metropolitan areas along the Texas–Mexico border, as well as for the Texas state regional economy.

To examine metropolitan BCI downturn predictability, the study uses yield spreads plus some other economic indicators that are potentially related to business cycle developments across Texas. Subsequent sections of the paper are as follows. The next section provides a brief overview of related studies. The following sections describes the methodological framework and data employed, and discusses empirical outcomes. Finally, we summarize principal results and implications for future research. Results obtained indicate the inclusion of the additional variables can be helpful and that metropolitan economic contractions may precede those of national or state economies.

Literature review

Previous research examines what information the term structures for US Treasury bill interest rates contain about future economic conditions in national economies. Research indicates that longer-term Treasury bill maturities have significant predictive power for future changes in inflation (Mishkin 1990). The yield spread, the difference between long-term and short-term treasury bills, has been found to serve as a valuable business cycle downturn forecasting tool. The yield spread tends to outperform other common recession indicators for a period of two to six quarters in the future (Estrella–Mishkin 1996). In further research, the yield spread by itself tends to be the only economic variable that reliably predicts recessions after one quarter (Estrella–Mishkin 1998).

Other research explores the ability of yield spreads to predict future economic conditions in developing economies. Gonzalez et al. (2000) determine that Mexican yield spreads have significant forecasting ability for inflation and real growth. Interestingly, the US and Euro area yield curves contain information about future inflation and growth in emerging economies. That especially holds true for countries with currency exchange rates that are pegged to the USD (Mehl 2009). Both studies indicate that the yield curve in emerging economies also contain information about future inflation and growth.

A substantial volume of recession predictability utilizing yield curves has been conducted for national economies. A smaller number of studies have examined this topic for state and regional economies in the United States. One such study finds that yield spreads can forecast multi-state regional economic downturns, but the effectiveness of downturn prediction varies according to regional economic structures (Gauger–Schunk 2002). Another study successfully modeled recessions in 34 of the 50 state economies in the United States in statistically reliable manners (Shoesmith 2003). Regional economic cycles is also a topic of international interest, with multiple areas of application. Recent examples include state-level crime fluctuations (Torres Preciado–Muriel Torrero 2021) and government budgets (Petrakos et al. 2021).

Forecasting economic conditions in US–Mexico border regions is a unique challenge because cross-border economic relationships affect metropolitan business cycles (Fullerton 2001). Those commercial and industrial ties include retail sector „exports," health sector tourism, as well as supply chain linked manufacturing, transportation, and warehousing activities (Phillips–Cañas 2008). Similarly, energy sector fluctuations are likely to play outsized roles in the business cycle that characterizes urban economic conditions in places like Houston. Consequently, the inclusion of variables that reflect those types of considerations may augment the information provided by yield spreads.

When available, BCIs provide useful means for understanding prevailing states of national, regional, or metropolitan economies. Stock–Watson (1991) develops a widely used BCI methodology known as dynamic single-index factor modeling that employs Kalman filters. This methodology develops BCIs under the assumption that the co-movements of key economic indicators are influenced by a common underlying, unobservable factor. This approach has been used to generate BCIs for various geographic regions. Among others, the latter include Texas (Phillips 2005) as well as border urban economies in that state (Phillips–Cañas 2008). Regional BCIs provide fairly up to date gauges of whether the economies analyzed are expanding or contracting.

A common approach to predicting the onset of economic contractions is to use binary recession indicators as dependent variables. Various studies indicate that the slope of the yield curve is the most reliable recession predictor (Dueker 1997). Incorporating lags of the binary recession indicators in the equation specifications has been found to significantly increase the predictive power of business downturn probit models (Kauppi–Saikkonen 2008, Nyberg 2010). To analyze metropolitan BCI downturn predictability, this study utilizes yield spreads from the US and Mexico, plus other regionally relevant economic variables, with parameter estimation carried out using a dynamic probit methodology. Dynamic and dynamic autoregressive probit models have been found to perform well in this context (Ng 2012, Fullerton et al. 2017).

Regional BCI modeling efforts may benefit from the inclusion of other variables that augment the information contained in the yield spread. For the border metropolitan economies, Mexican yield spreads and peso/USD currency exchange rates are likely to help predict BCI downturns because economic condition in Mexico also affect the business conditions on the north side of the boundary (Fullerton 2001, Fullerton et al. 2017). Oil prices are a useful indicator for predicting business cycle downturns in economies with substantial energy activities (Lee 2015). For example, in the petroleum driven economy of Midland–Odessa, oil price fluctuations tend to correspond with similar shifts in local BCIs (Downs–Fullerton 2017).

The objective of this study is to develop probit downturn models for the five largest urban economies in Texas, the four largest metropolitan areas along the Texas-Mexico border, as well as the Texas state economy. The five largest urban economies in Texas are Austin-Round Rock, Dallas-Plano-Irving, Fort Worth-Arlington, Houston-The Woodlands-Sugarland, and San Antonio-New Braunfels. The four largest metropolitan areas along the Texas-Mexico border are Brownsville-Harlingen, El Paso, Laredo, McAllen-Edinburg-Mission.

Data and methodology

Probit analysis is used to quantify the probability of recessions in a particular time period. This approach has been used to model business cycle contractions in multiple geographies. A static probit model can be written as follows:

$$\Pr(Y_t = 1) = F(\beta_0 + \beta_1 X_{t-k}) \tag{1}$$

In Equation (1), *Pr* is the probability of an existing recession (Yt = 1 if a recession is underway at time t, 0 if not), X_{t-k} is an explanatory variable at time $t-k$, β_0 and β_1 are parameters to be estimated, and F represents the cumulative normal distribution function.

One drawback of the static model is that it does not take advantage of autocorrelated information potentially embedded within the binary recession indicator. In such cases, dynamic probit model specifications take into account prior states of the economy by including a lag of the dependent variable as shown in Equation (2).

$$\Pr(Y_t = 1) = F(\beta_0 + \beta_1 X_{t-k} + \beta_2 Y_{t-\mathrm{m}}) \tag{2}$$

Dueker (1997) argues that the dynamic version of the probit model is better suited to handling problems such as serial correlation that frequently arise in the context of time-series modelling. Along those lines, Kauppi–Saikkonen (2008) find that dynamic probit models tend to outperform static specifications for predicting national economic downturns in the United States. The model in Equation (2) can be further augmented by introducing additional explanatory variables. Standard selection criteria such as pseudo-R^2 statistics can be used to identify which lags of candidate explanatory variables to include in an equation (Nyberg 2010).

To help select an estimated equation functional form, the pseudo-R^2 metric developed by Estrella–Mishkin (1998) is employed. The metric is calculated as shown below.

$$\text{Adjusted Pseudo - R}^2 = 1 - \left(\frac{L_u}{L_c}\right)^{-\left(\frac{2}{n}\right)L_c} \tag{3}$$

In Equation (3), L_u is the unconstrained maximum value of the log-likelihood, L_c is the constrained maximum value of the log-likelihood assuming all coefficients except the constant are zero, and n is the sample size. Standard diagnostic statistics such the t-statistic are also utilized.

The modelling framework employed in this study analyzes probabilities of BCI downturns for selected urban economies located in Texas as functions of yield-spreads as well as other regional and macroeconomic variables. This study employs business cycle indices for the five largest economies in Texas, the four largest metropolitan areas along the Texas-Mexico border, as well as a regional BCI estimated for the Texas state economy. The other regional and macroeconomic variables are included based on characteristics of the economies being analyzed.

The five largest economies in Texas all engage in energy activities or are greatly affected by energy prices (FRBD 2014). As noted above, oil prices can help predict business cycle fluctuations in economies with substantial energy activities (Lee 2015). Accordingly, West Texas Intermediate oil prices are included as part of the sample data collected for those five urban economies.

In the four largest metropolitan economies along the Texas-Mexico border, this study utilizes a framework similar to that outlined by Fullerton (2001). In that study, border region economic performance is modelled as a function of both national and international variables. Subsequent studies have confirmed that the peso/USD exchange rate strongly influences business activity along the border (Patrick–Renforth 1996, Coronado–Phillips 2007, Niño et al. 2015). Yield spreads for the United States and Mexico are also included in the specifications for each of these border economies.

The dichotomous dependent variables identify downturns in each metropolitan economy. According to Klein–Moore (1983), the binary variables are constructed using monthly frequency regional BCI values. In all nine economies, the binary dependent variable is defined by shifts in the business cycles indices. If there is a recession, the binary dependent variable for that specific month is equal to one. If there is not a business cycle contraction, this variable is equal to zero. For the four urban economies located on the border, the BCIs are measured for the Texas side of the border (Phillips–Cañas 2009).

For purposes of this study, a recession is defined as six consecutive months (or more) of negative growth in a BCI. An economic contraction ends after six consecutive months of positive growth in a BCI. This simple definition works well for the sample period employed, but readers should note that it may not work for all time periods or all regions. For example, this definition implies that a sequence of six monthly downward movements, followed by five monthly upward changes, and six subsequent downward movements represents a 17-month recession. That interpretation seems reasonable, but an official business cycle dating committee might determine that two recessions separated by a short expansion is what has actually occurred under those circumstances. At present, regional dating committees do not exist for Texas or any other sub-national regions in the United States.

The United States yield spread is calculated as the 10-year Treasury bond rate minus the 3-month Treasury bill rate. All United States interest rate data are from the Federal Reserve Bank of St. Louis (FRED 2018). The yield spread of Mexico is calculated as the 1-year Treasury bill rate minus the 28-day Treasury bill rate (CETES). All Mexican interest rate data are from the central bank of Mexico (BM 2018a). This study utilizes the above Mexican yield spread and a peso/USD (MXN/USD) real exchange rate index because economic conditions in Mexico sometimes have pronounced impacts on the business cycles of the United States border cities (BM 2018b, Phillips–Cañas 2008). These international economic variables are important for this research because the cities selected for this study and their cross-border counterparts in Mexico share a variety of commercial and industrial linkages. The dependent variable takes a lag of one in order to capture potential autocorrelation structures of the dependent variables (Ng 2012). Additionally, experimentation is also conducted with an alternate lag structure of three months that Dueker (1997) posits as the minimum recognition lag time for recessions.

Three different specifications employing the dynamic probit framework are proposed. Equation (4) is used for the five largest urban economies in Texas. Equation (5) is employed for the four border metropolitan economies. Equation (6) is utilized for the Texas state business cycle.

$$\Pr(Y_t = 1) = F(\beta_0 + \beta_1 USSP_{t-k} + \beta_2 WTI_{t-h} + \beta_3 Y_{t-m} + \varepsilon_t) \quad (4)$$

$$\Pr(Y_t = 1) = F(\beta_0 + \beta_1 USSP_{t-k} + \beta_2 MXSP_{t-h} + \beta_3 REX_{t-i} + \beta_4 Y_{t-m} + \varepsilon_t) \quad (5)$$

$$\Pr(Y_t = 1) = F(\beta_0 + \beta_1 USSP_{t-k} + \beta_2 MXSP_{t-h} + \beta_3 REX_{t-i} + \beta_4 WTI_{t-j} + \beta_5 Y_{t-m} + \varepsilon_t) \quad (6)$$

Table 1

Description of the variables

Variable name	Description	Hypothesized coeff. sign
USSP	US Yield Spread	(–)
WTI	Real West Texas Intermediate Oil Price, USD/bbl	(–)
Y	Business Cycle Recession Indicator	(+)
MXSP	Mexico Yield Spread	(–)
REX	Real Exchange Rate Index, pesos per USD	(+ or –)

Table 1 summarizes the hypothesized relationships between the recession indicator, Y, and each of the explanatory variables. In Equations (4) through (6), *USSP* is the United States yield spread, *WTI* is the real monthly West Texas Intermediate Crude Oil Spot Price in USD per barrel, Y_{t-m} is the binary dependent variable with a lag of *m* months, *MXSP* is the yield spread for Mexico, and *REX* is the inflation adjusted peso/USD exchange rate index. The corresponding model is estimated for each of the metropolitan economies mentioned above in the previous section. Because REX is defined in peso per USD terms, the numeric value of REX occurs as a consequence of real peso appreciation against the USD. The converse also holds.

Equation (4) is used to examine whether the yield spreads and monthly real spot prices of WTI oil can help predict recessions in the five largest Texas metropolitan economies. For the inflation adjusted WTI, the nominal WTI spot prices are deflated by dividing those data by the United States consumer price index (base period, 1982–84 = 1.00). A decrease in the United States yield spread, which results from higher short-term interest rates and/or lower long-term rates, is hypothesized to increase the probability that a recession will occur in future quarters (this is also posited for Equations (5) and (6)). That is because high short-term interest rates are often associated with contractionary monetary policy and lower long-term rates may reflect expectations of an economic slowdown in coming years (Dueker 1997). A decrease in the spot prices of WTI oil is hypothesized to increase the probability a recession will occur in future quarters. That is because low oil prices dampen growth within the energy sector which hurts the Texas economy as a whole. Of course, inclusion of WTI may also be germane to business cycle analysis for non-oil producing regions. In those cases, unlike that of Texas, a decrease in WTI would *reduce* the likelihood of a future downturn (Francis et al. 2018).

Equation (5) is used to examine whether the yield spreads and the real exchange rate index can help predict recessions in the four largest metropolitan economies along the Texas-Mexico border economies comprised in the sub-sample. For similar reasons to the United States yield spread, the yield spread for Mexico is expected to have an inverse relationship with the probability of recession. Economic slowdowns in Mexico may coincide with downturns in cities on the north side of the border for a variety of reasons. First, retail sectors in many United States border cities rely on a steady influx of Mexican shoppers. Those sales tend to decline when such shoppers reduce consumption, as typically occurs when Mexico faces a recession (Coronado–Phillips 2007, Phillips–Cañas 2008). Other border region economic sectors such as freight transportation, wholesale trade, and financial services conduct business with manufacturers located in Mexico (Cañas et al. 2013). Thus, a higher probability of recession in Mexico, as signaled by a flattening or inversion of that country's yield curve, is hypothesized to increase the probability of recession on the north side of the border.

The impacts of real exchange rate on border city economies is ambiguous. Some prior research suggests that peso depreciations can have strong adverse impacts on retail sectors in the United States border cities (Patrick–Renforth 1996). However, peso depreciations also tend to stimulate export-processing activity in Mexican border cities, which may help fuel economic activity on the north side of the border (Niño et al. 2015). If a real depreciation of the peso lowers the probability of recession for any of the border economies examined, then the exchange rate coefficients will be negative. The converse will occur if peso weakness increases the likelihood of a business cycle downturn.

Equation (6) is used to examine whether the yield spreads, the real exchange rate index, and the spot prices of WTI oil can help predict recessions for the Texas state economy. The impacts of fluctuations in these variables on the metropolitan economies in the sample are discussed above. Equation (6) reflects many aspects of the modern Texas economy, regionally, nationally, and internationally.

Empirical analysis

Equations with varying specifications are estimated for each economy. The final specifications are selected by taking into consideration pseudo-R^2 values, lag length information criteria, coefficient statistical significance, and other statistical diagnostic tools (Gauger–Schunk 2002, Nyberg 2010). Initial dependent variable lag specifications of one month are sub-optimal when compared to the alternate dynamic lag specification of three months. Sample data employed are from January 1991 to May 2018, a span of about 27 years. Primary estimation results are summarized in Tables 2 through 7. It should be noted that the differing lag structures and equation specifications reported indicate that the state and metropolitan economies in this study exhibit distinct timing features and follow different business cycle paths. That corroborates what has been documented for individual business cycle models estimated for different regions in Europe (Gómez-Loscos et al. 2020).

In general, Equations 4 through 6, outlined in the previous section, deliver favorable estimation results. Given the geographic location of Laredo on the Eagle Ford shale formation, an alternate model is specified by including the West Texas intermediate oil price as an explanatory variable. Fort Worth, Laredo, and the Texas economies are the only economies that deviate from the general equation specifications outlined in the previous section. The coefficient sign for West Texas intermediate oil prices in Fort Worth and Texas were positive which runs counter to conventional wisdom. It is, therefore, removed from the model specification for those economies.

A positive coefficient for West Texas intermediate oil prices also results when it is included in equations estimated for Laredo. The version summarized in Table 2 exhibits much better statistical traits than other specifications, as well as more realistic coefficients for the other regressors. Alternative specification outcomes for all of the regions analyzed are included in the Appendix.

As hypothesized, all of the US yield spread parameter estimates in Tables 2, 4, and 6 are negative. Each of the USSP coefficients are also statistically significant at the

1-percent level. The United States yield spread can predict recessions for metropolitan economies with leads of 13 to 26 months. Many prior studies, for both national and state economies, suggest lead times of 6 to 18 months (Dueker 1997, Estrella–Mishkin 1996, 1998, Shoesmith 2003). In Table 7, the lead times for Texas and San Antonio fall within that range. Lead times in Tables 3, 5, and 7 for the other metropolitan economies are, however, more in line with longer leads documented elsewhere for regional economies in the United States (Fullerton et al. 2017, Gauger–Schunk 2002) and for emerging economies elsewhere (Mehl 2009). Those outcomes raise the interesting possibility that business cycle downturns can be anticipated earlier for urban economies than for regional and/or national economies, at least in high income areas of the globe.

Table 2

Estimation results for Texas border metropolitan economies

Denomination	El Paso	Laredo	McAllen	Brownsville
Coefficient	14.550***	–0.270	6.345***	9.395***
USSP	–3.184***	–0.383***	–0.381**	–1.220***
MXSP	–0.426***	–0.212**	–0.874***	–1.316***
REX	–0.167***	–0.0015	–0.086***	–0.111***
WTI		0.0098***		
Yt-3	2.827***	1.931***	4.399***	2.3203***
Akaike Inf. Crit.	0.173	0.726	0.245	0.181
Hannan Quinn Crit.	0.198	0.756	0.269	0.205
Schwartz Inf. Crit.	0.235	0.799	0.306	0.242
Log-likelihood	–21.187	–105.52	–32.085	–22.414
Restr. Log-likelihood	–119.95	–193.75	–169.56	–100.03
Total Obs.	302	307	303	303
Obs. Dep = 0	261	207	228	272
Dep = 1, Recession	41	100	75	31
Pseudo R-squared	0.823	0.455	0.811	0.776

Notes: The sample period is January 1991 to May 2018.
* Statistically significant at 10%.
** Statistically significant at 5%.
*** Statistically significant at 1%.

Table 3

Lag selection for Texas border metropolitan economies

Denomination	El Paso	Laredo	McAllen	Brownsville
USSP	–26	–21	–25	–25
MXSP	–6	0	–9	–1
REX	0	–8	–8	–5
WTI		–20		
Yt-3	–3	–3	–3	–3

Table 4

Estimation results for largest Texas metropolitan economies

Denomination	Austin	Dallas	Fort Worth
Coefficient	0.618	0.368	–1.066**
USSP	–1.831***	–1.647***	–2.688***
MXSP			
REX			
WTI	–0.065**	–0.056*	–0.013
Yt-3	4.457***	5.184***	7.640***
Akaike Inf. Crit.	0.191	0.200	0.145
Hannan Quinn Crit.	0.211	0.219	0.164
Schwartz Inf. Crit.	0.241	0.249	0.193
Log-likelihood	–24.309	–25.633	–18.363
Restr. Log-likelihood	–120.88	–126.32	–93.923
Total Obs.	296	297	309
Obs. Dep = 0	254	252	281
Dep = 1, Recession	42	45	28
Pseudo R-squared	0.799	0.797	0.804

Notes: The sample period analyzed is January 1991 to May 2018.
* Statistically significant at 10%.
** Statistically significant at 5%.
*** Statistically significant at 1%.

Table 5

Lag selection for largest Texas metropolitan economies

Denomination	Austin	Dallas	Fort Worth
USSP	–19	–19	–18
MXSP			
REX			
WTI	–32	–31	–19
Yt-3	–3	–3	–3

Table 6

Estimation results for Texas metropolitan economies and state economy

Denomination	Houston	San Antonio	Texas
Coefficient	–0.174	0.536	–1.152***
USSP	–2.400***	–1.919***	–0.837***
MXSP			–0.097**
REX			
WTI	–0.048**	–0.056*	
Yt-3	8.883***	4.314***	3.277***
Akaike Inf. Crit.	0.157	0.185	0.224
Hannan Quinn Crit.	0.176	0.205	0.243
Schwartz Inf. Crit.	0.206	0.235	0.271
Log-likelihood	–20.187	–23.445	–31.231
Restr. Log-likelihood	–115.07	–119.07	–82.332
Total Obs.	308	296	315
Obs. Dep = 0	270	255	292
Dep = 1, Recession	38	41	23
Pseudo R-squared	0.825	0.803	0.621

Notes: The sample period analyzed is January 1991 to May 2018.
* Statistically significant at 10%.
** Statistically significant at 5%.
*** Statistically significant at 1%.

Table 7

Lag selection for Texas metropolitan economies and state economy

Denomination	Houston	San Antonio	Texas
USSP	–20	–22	–13
MXSP			–6
REX			
WTI	–1	–32	
Yt-3	–3	–3	–3

Fullerton et al. (2017) speculates that what may help explain the long lead times for some urban border economies is the relatively large role of the public sector in these economies. Government expenditure patterns will offset and delay the local impacts of national downturns due to public budgeting mechanics. During the sample period, government payrolls represent 23.7 percent of total employment in the border economies, 16.0 percent in the largest Texas economies, 17.2 percent of employment in the Texas state economy, and 16.3 percent in the national economy (BLS 2019). The lag structures displayed in Tables 3, 5, and 7 somewhat validate the aforementioned relationship between longer USSP lead times and the magnitude of public sector employment. The average lead time for the selected border economies in the study is 24 months, while the average lead time for the largest Texas metropolitan economies is 21 months, and that for the Texas state economy is 13 months.

In Table 2 and 6, all of the Mexico yield spread parameter estimates are also negative as hypothesized. Most are statistically significant at the 1-percent level. For the economies where this variable is included (Texas and the border economies), the lead times for MXSP are shorter than those for USSP. MXSP is included with contemporaneous, 6-month, or 9-month lags. These shorter lead times may be attributed to the fact that the Mexico yield spread is calculated as the 1-year Treasury bill rate minus the 28-day Treasury bill rate (CETES). That varies substantially from the USSP measure calculated as the difference between the 10-year Treasury bond rate and the 3-month Treasury bill rate. The lead times for MXSP align closely with those reported in other studies (Fullerton 2017, Reyna-Cerecero et al. 2008).

The results in Table 2 indicate that real depreciation of the peso against the USD decreases the probability of a recession in all four of the border economies. As previously stated, peso depreciations tend to stimulate export-processing activity in northern border municipalities in Mexico (Coronado et al. 2004, Cañas et al. 2007, Niño et al. 2015). That generally leads to increased economic activity in the adjacent metropolitan areas on the northern side of the international boundary (Hanson 1996, Varella-Mollick et al. 2006, Cañas et al. 2013). The negative REX coefficients provide additional evidence along those same lines.

Nearly all of the West Texas intermediate spot oil price parameter estimates for the metropolitan economies are negative. The exception is the WTI coefficient estimated for Laredo. As stated at the beginning of this section, oil prices are included in the specification of this border economy because of its presence on the Eagle Ford Shale formation. The positive parameter is puzzling. Laredo has a very high concentration of employment in transportation and warehousing. Across the border, and closely linked to that segment of the Laredo metropolitan economy, are large manufacturing sectors in both Monterrey and Nuevo Laredo. Transportation and manufacturing are energy intensive sectors and that may be what leads to the positive correlation between oil price hikes and recessions in the former Rio Grande Republic. As more data become available, additional research appears warranted.

The marginal effects for each equation are reported in Table 8. Not surprisingly, the largest marginal effects are calculated for USSP and the 3-month autoregressive lag of the dichotomous recession indicator. Those outcomes confirm many of the earlier studies using national economic data. The MXSP marginal effects are also fairly large for three of the border economies, but not for Laredo. The latter outcome is surprising because the economic fortunes of Laredo are heavily influenced by manufacturing conditions in Monterrey, Nuevo León and Mexico as a whole. The WTI marginal effects are also fairly low, but Texas economic diversification makes those outcomes less surprising. The marginal effect reported for REX is also relatively small for Laredo. Given the importance merchandise trade and exported retail sales in Laredo (Coronado–Phillips 2007), the REX magnitude is unexpectedly modest.

There is substantial hetereogeneity in the estimation results presented in Tables 2 through 8. Given the different industry mixes present in each of the metropolitan economies included in the sample, that is not surprising. The differences in the lags and the marginal effects for the Texas state economy and each of the urban areas is reminiscent of results documented regarding the United States national economy and the various state economies throughout the country (Owyang et al. 2005). If the lag structures and marginal effects.

Table 8

Calculated marginal effects

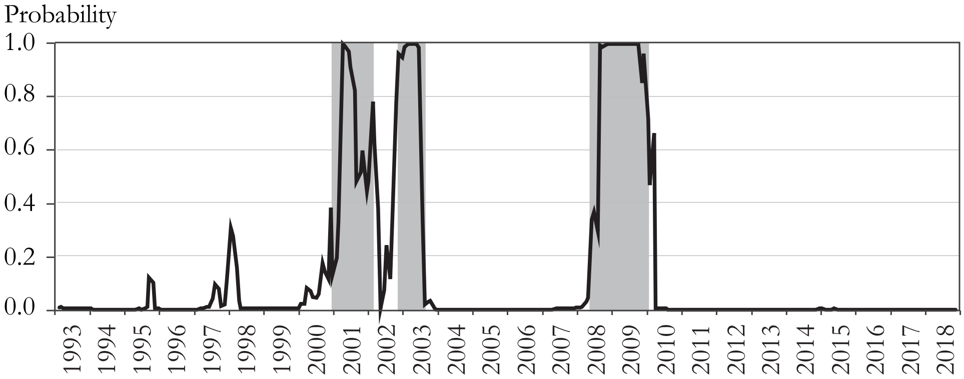
Denomination	USSP	WTI	MXSP	REX	Y(–3)
El Paso	–0.4993		–0.1648	–0.0633	0.4976
Laredo	–0.1492	0.0039	–0.0840	–0.0006	0.4733
McAllen	–0.1484		–0.3088	–0.0342	0.4999
Brownsville	–0.3887		–0.4059	–0.0444	0.4955
Austin	–0.4664	–0.0258			0.4999
Dallas	–0.4502	–0.0222			0.5000
For Worth	–0.4964	–0.0050			0.5000
Houston	–0.4918	–0.0193			0.5000
San Antonio	–0.4725	–0.0225			0.4999
Texas	–0.2988	–0.0385			0.4995

In-sample simulations are employed in order to examine how well each of the models can predict business cycle downturns. Figure 1 shows the actual and fitted values of the binary recession indicator for each economy analyzed. The graphs measure recession probabilities on the vertical axis with shading used to indicate when actual economic contractions occurred. Various different probability thresholds are utilized in different studies to identify potential downturn periods. Generally, recession signals above 0.5 (50 percent) are considered strong signals for downturns (Ng 2012, Nyberg 2010). Some research classifies values as low as 0.25 (25 percent) as weak signals. In those cases, the consequences of failing to predict an oncoming recession are greater than falsely anticipating a downturn that never occurs (Dueker 2002).

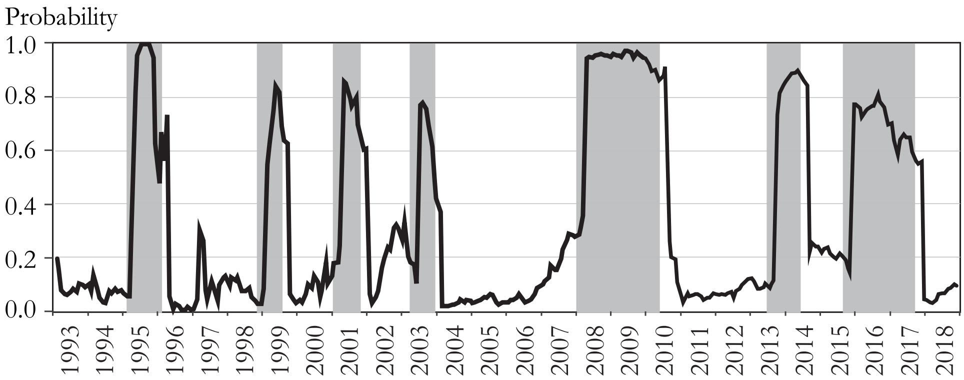
Figure 1

Actual and fitted values for each economy analyzed

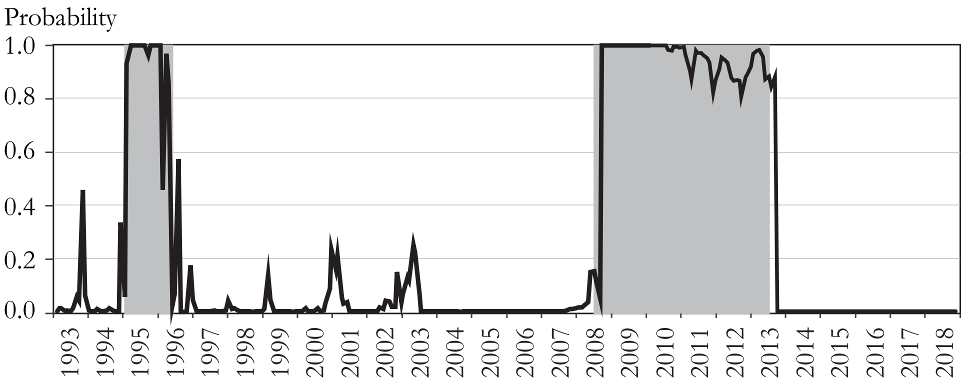
El Paso (MSA)



Laredo (MSA)



McAllen-Edinburg-Mission (MSA)



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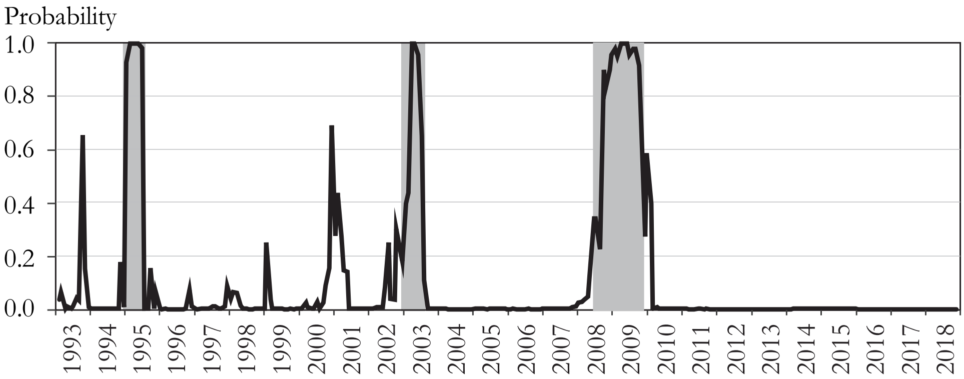
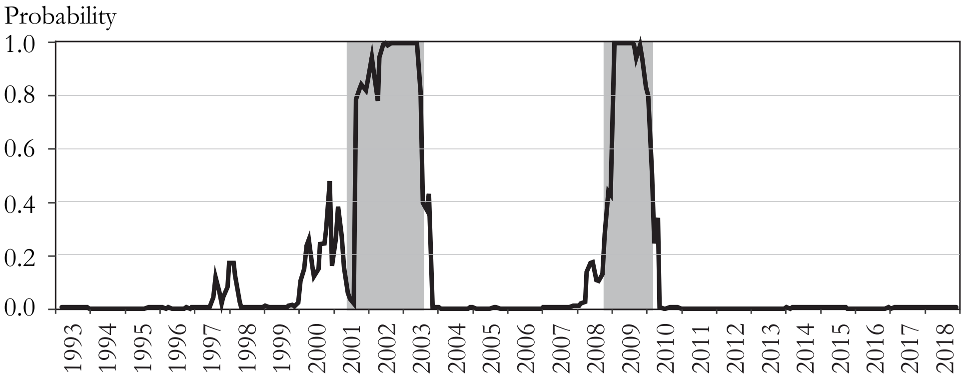
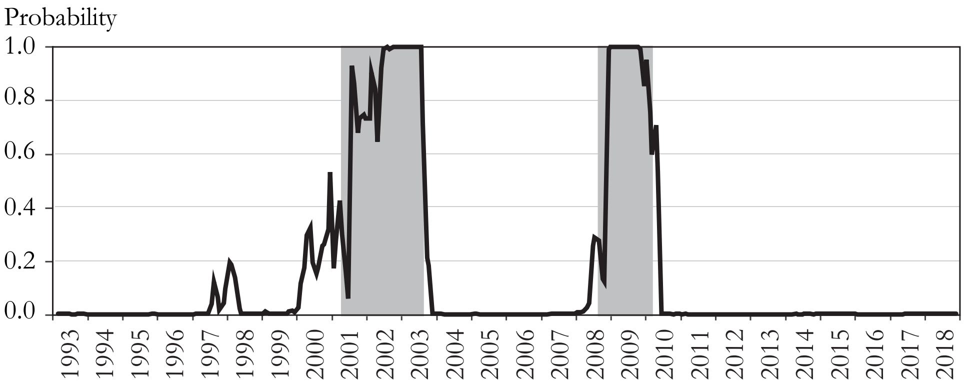
Brownsville-Harlingen (MSA)



Austin-Round Rock (MSA)



Dallas-Plano-Irving (Metropolitan Division)



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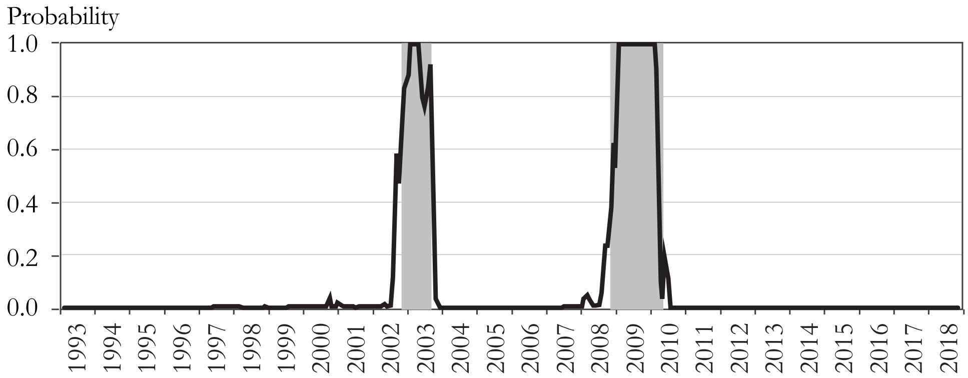
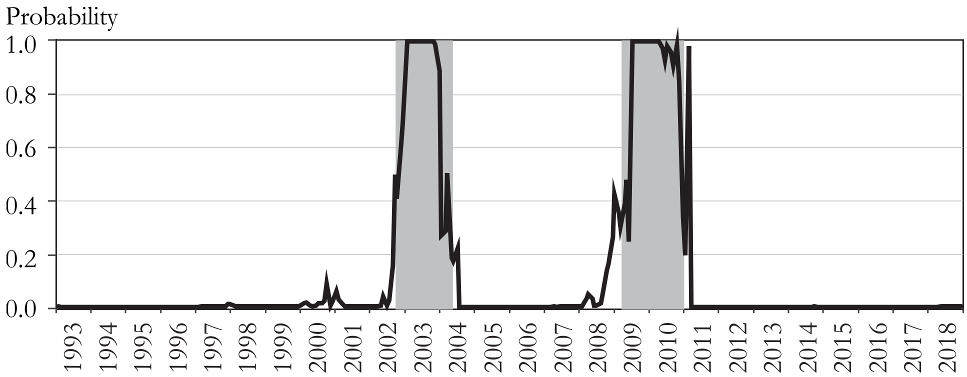
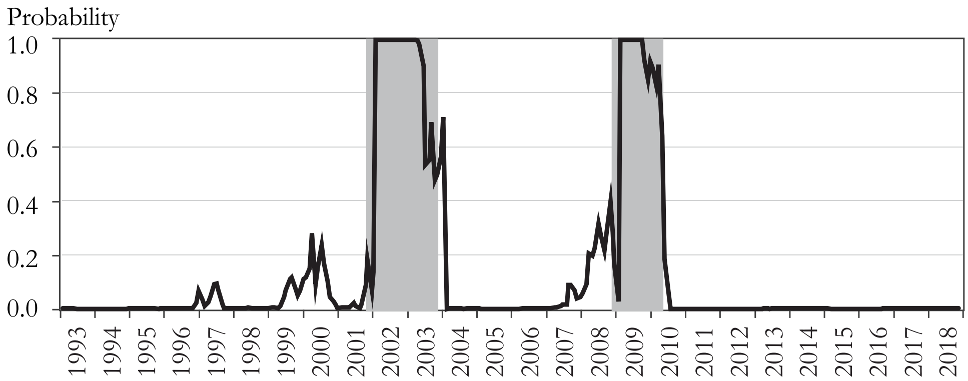
Fort Worth-Arlington (Metropolitan Division)



Houston-The Woodlands-Sugar Land (MSA)



San Antonio-New Braunfels (MSA)



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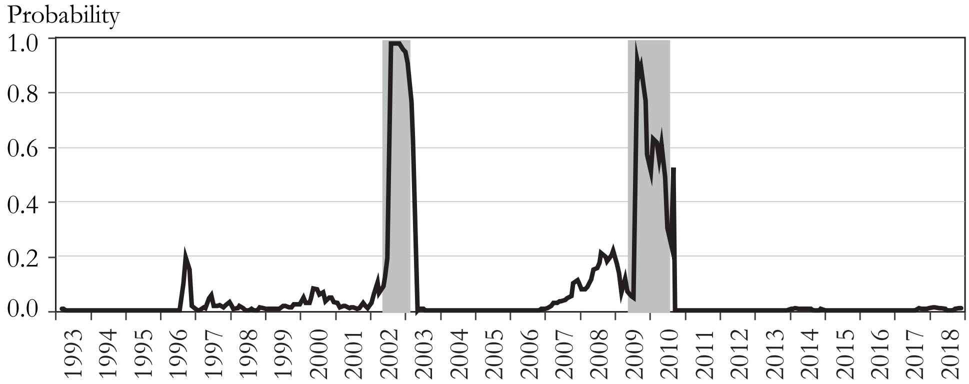
Texas (State)



The dynamic probit models estimated for each Texas economy in the sample provide generally adequate information regarding the probability of business cycle downturns. In most cases, when the predicted probabilities exceed 0.5 (50 percent), recessions occur. In contrast, the predicted probabilities tend to stay below 0.5 when the economies are growing. The in-sample recession forecasts do have some missteps. In 2000, two of the equation simulations generated false signals for slumps that never materialized. Those false signals are for the Brownsville border economy and the Dallas metropolitan economy.

Conclusion

Regional and metropolitan business cycle indices are not widely available, but several variables are estimated for Texas and nine of the largest urban economies in that state. Modeling and predicting recessions in Texas, however, offers a special challenge. The state is so large that the various urban economies located in Texas exhibit unique business cycle idiosyncrasies. Given the importance of international trade in Texas, many urban economies in the state are affected by domestic and international factors. This study attempts to allow for these factors using domestic and foreign yield spreads, a real peso per USD exchange rate, West Texas Intermediate oil prices, and a dynamic lag variable. To date, there have been few economic downturn prediction efforts conducted for metropolitan economies. Among the regional business cycle studies that have been completed, yield spreads have been shown to reliably predict recessions.

The United States yield spread is also found to predict slumps in all of the economies analyzed in this study. Confirming relatively important cross-border industrial and commercial linkages, Mexico yield spread is found to help anticipate economic contractions for all four border economies as well as for the Texas state economy. Unexpectedly, the real peso per USD exchange rate index is a reliable predictor of business cycle downturns for only two of the four border economies. Somewhat surprisingly, West Texas Intermediate oil price declines help predict economic slumps for four of the large urban economies, but not for the state as a whole. Finally, the 3-month dynamic lag specification performs more reliably than the 1-month dynamic lag specification, offering regional evidence that three months is the minimum recognition lag time for recessions. In-sample simulations indicate that the estimated models exhibit good predictive behavior with only minimal false signal emissions.

Future research may benefit from more Mexico yield spread data. Although Mexico does have a term structure, yields on government bonds with maturities of longer than three years only date from 2000 forward. As more yield spread observations become available, that may contribute better information regarding the onset of regional downturns in Texas. More broadly, metropolitan business cycle index estimation has fairly minimal data requirements. These indices provide useful information to policymakers and business analysts. As the procedure is extended to analyze more regions, further research on business cycle predictability will become feasible. The evidence obtained on this study indicates some metropolitan downturns occur before national recessions. Accordingly, metropolitan early warning signals may allow safe deployment of lower short-term interest rate plus quantitative easing monetary policy actions without triggering higher bouts of inflation as means for pre-emptively reducing national economic contractions.

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Appendix

Yield spreads and business cycle downturn predictability across Texas: EViews average marginal effects calculation code

1) Click on "Proc" tab in the equation estimation output, Forecast, "Index – where Prob= 1-F(-Index)", save it as abbreviated "CityF"
2) Multiply the coefficient on the variable of Interest by City = @dnorm (-@mean(CityF)); done by clicking on Genr
3) Create dummy variable of 1, name it DV1
4) Run the following code:
   a. equation city_eq.fit(city) cityf
   b. scalar meanxb = @mean(cityf)
   c. scalar meandum1 = @mean(dv1)
   d. scalar meanxb0 = meanxb - city_eq.c(2)*meandum1
   e. scalar meanxb1 = meanxb + city_eq.c(2)*(1 - meandum1)
   f. scalar meffect1 = @cnorm(meanxb1) - @cnorm(meanxb0)

   * Where c(2) is the number of the coefficient being analyzed.

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