The Differential Impact of the U.S. and Mexican Economic Performance on the Employment Figures in Texas

Chrystell Flota
The University of Texas-Pan American

Gökçe A. Soydemir
The University of Texas-Pan American

Working Paper #2002-3
July 2002

Center of Border Economic Studies
The University of Texas-Pan American

The differential Impact of the U.S. And Mexican Economic Performance on the Employment Figures in Texas

Chrystell Flota
The University of Texas-Pan American

Gökçe A. Soydemir
The University of Texas-Pan American

Working Paper #2002-3
July 2002

This article is released as part of the Working Papers Series of the Center for Border Economic Studies (CBEST) at The University of Texas-Pan American. CBEST is a research unit of UTPA dedicated to finding solutions to the economic problems unique to the U.S./Mexico border region. The Center conducts policy-oriented research in four key areas: (1) Regional economic development and trade, (2) Labor market and immigration, (3) Health and environmental policy, and (4) Information technology.

The UTPA CBEST Project is funded through Economic Adjustment Assistance, Project No. 08-79-03628, Economic Development Administration, U.S. Department of Commerce. The statements, findings, and other data in this report are solely those of the authors and do not necessarily reflect the views of the Economic Development Administration.

Center for Border Economic Studies
The University of Texas-Pan American

Address	**1201 W. University Dr.**
	Edinburg, Texas 78539
Telephone	**956.318.5371**
Fax	**956.381.2322**
Internet	**www.c-best.org**

THE DIFFERENTIAL IMPACT OF THE U.S. AND MEXICAN ECONOMIC PERFORMANCE ON THE EMPLOYMENT FIGURES IN TEXAS

Chrystell Flota
The University of Texas-Pan American

Gökçe A. Soydemir*
The University of Texas-Pan American

Working Paper #2002-3
July 2002

Abstract: *In this paper, we investigate whether regional employment figures from Texas are differentially impacted by the national key economic variables from Mexico and the U.S. by constructing a four variable vector autoregression (VAR) model. We find that Texas non-farm employment responds in a more rapid and sustained fashion to a one-time shock in the industrial production index of the U.S. than Mexico. However, Texas non-farm employment responses are also found to be statistically significant to movements in the Mexican industrial production index and Mexican imports from the U.S. Our findings are consistent with the view that because of the socioeconomic interdependence along the Texas-Mexico border, the economic activity in Mexico serve to impact employment in Texas albeit less but nevertheless significantly than the U.S. national economic indicators.*

Keywords: Texas Economy, Employment, VAR Model, Regional Interdependence

---

Chrystell Flota, Department of Economics and Finance, College of Business Administration, University of Texas-Pan American, Edinburg, Texas USA 78539. Gökçe A. Soydemir, Department of Economics and Finance, College of Business Administration, University of Texas-Pan American, Edinburg, Texas USA 78539; Tel: 956.381.2830; soydemir@panam.edu

*Corresponding author. We thank Alberto Dávila for valuable comments and suggestions.

I. Introduction

After the recent elections in Mexico, the newly elected president Vicente Fox has pledged, as an utmost priority, to make Mexico even a more open economy by promoting free trade and foreign direct investment. Earlier literature on the U.S.-Mexico border concludes that the Texas-Mexico region is “an extreme case of an enclave” because of high socioeconomic interdependence among the cities located along both sides of the border (Dávila and Mora, 1997). Thus, the issue of whether Texas is likely to benefit from the recent developments taking place in Mexico is increasing in importance. Given these developments, it may be assumed that forecasts related to employment in the state of Texas could be improved by incorporating information related to the Mexican economy. From a public policy standpoint, this study can assist local policy makers in anticipating and adapting to business cycle-related fluctuations in critical sectors of the local economy better by taking into account regional impact of the neighboring economy. With this purpose, we develop a vector autoregressive (VAR) model to investigate whether regional employment figures from Texas are impacted by the national key economic variables from Mexico and the U.S.

We find that Texas non-farm Employment responds rapidly to a one-time shock in the U.S. industrial production index, which remains sustained for three months. Texas non-farm Employment response is also found to be statistically significant to movements in the Mexican industrial production index and Mexican Imports from the U.S. allowing us to conclude that Mexican key economic indicators are also an important determinant of Texas non-farm employment. Our findings are consistent with the view that socioeconomic interdependence that exists among cities along the Texas-Mexico border serves to influence non-farm employment in Texas in as much as the U.S. national economic indicators, given the border's geographical proximity to Mexico.

The remainder of the paper is organized as follows. Section II presents the theoretical framework, section III describes the data and the model used in the study. Section IV provides the estimation results and section V concludes.

II. Theoretical Framework

In this section, we establish a Keynesian type theoretical framework to address the role of aggregate demand in determining output and employment in the Texas economy. We begin with the assumption that there exists an employment level, which corresponds to the equilibrium level of GDP at the income-expenditure equilibrium. Further, if there exist autonomous and induced components of real GDP in an economy, then there must also be employment levels that correspond to these components, which we shall call autonomous and induced employment. For perspective, when a given firm in the region hires a thousand workers and pays income for their services, these workers in turn generate induced employment when they spend their income in other goods. The autonomous and induced employment can be represented as,

$$AE_t = A_t + \delta E_t \tag{1}$$

$$A_t = \alpha_0 + \alpha_1' Y_t + \alpha_2' Z_t + \alpha_3 E_{t-1} \tag{2}$$

Where, AE_t is aggregate employment in the region at time t, the first and second terms on the right hand side of equation (1) represent autonomous and induced consumption, respectively. Y_t is a (Nx1) vector of the U.S. and Mexican national macroeconomic variables, such as the industrial production indexes of both countries, and the composite index of leading indicators, α_1 is a (1xN) vector of parameters and Z_t

is a (Kx1) vector of regional variables, α_2 is (1xK) vector of parameters where K can be equal to N. After substituting, the equations above can be represented as,

$$AE_t = \alpha_0 + \alpha_1 y_t + \alpha_2 z_t + \alpha_3 x_t \delta E_t + \alpha_4 E_{t-1} \tag{3}$$

For which the parameters can be estimated using conventional econometric methods. Solving this equation for E_t at the equilibrium where total expenditure (AE) equals Real GDP[1], the corresponding multipliers can be found due to a change in each component of A.

$$\delta E_t / \delta Y_{1_t} = \alpha_{11} / (1-\delta) \tag{4}$$

$$\delta E_t / \delta Z_{1_t} = \alpha_{21} / (1-\delta) \tag{5}$$

$$\delta E_t / \delta E_{t-1} = \alpha_3 / (1-\delta) \tag{6}$$

Thus, a one unit exogenous increase in local employment due to an increase in the U.S. or Mexican macroeconomic variable would generate employment in the region by $\alpha_{11}/1\text{-}\delta$ amount, which we shall call the employment multiplier. The model with the better forecasting accuracy produces also a more accurate multiplier. This allows us to focus on forecasting performance, as opposed to the estimation of the multipliers, in line with the expressed objectives of this article.

III. The Data and Econometric Methodology

The data on Texas employment by sector are obtained from the Bureau of Labor Statistics and the data for Mexican imports from the U.S. is obtained from the U.S. Department of Commerce as reported in DataStream. The industrial Production Indexes for both the U.S. and Mexico are from the OECD databases are also obtained from DataStream. The sample period covers a seventeen-year span from January 1983 to February 2000. Given the number of observations relative to the loss of degrees of freedom and to avoid the problem over parameterization in the VAR model (Enders, 1995; Doan, 1997), we decide to include only the two of the most important economic indicators of the Mexican economy.[2]

Before the estimation stage we determine whether the data are stationary (Enders, 1995) by using the augmented Dickey-Fuller (ADF) test. Table 1 reports the results of the ADF tests of the variables in the VAR model. If the t-statistic exceeds the tabulated critical value, the null hypothesis of a unit root is rejected against the one-sided alternative. If the test fails to reject the null hypothesis of a unit root in the series at any of the reported significance levels, then the series is non-stationary. MacKinnon (1991) provides critical values for rejection of hypotheses of a unit root. The series in logarithmic first differences for the four variables --total non-farm Employment, Mexican industrial production index, the U.S. industrial production index, and Mexican Imports from the U.S.-- were found to be stationary at the 1% significance level. The next step is to test for cointegration to determine whether a linear combination of the non-stationary series is stationary. Testing for cointegration is only valid when the series used in the model are known to be non-stationary. The unit root tests applied above to test for stationarity show that the four variables used in this model integrated of order one; hence, the stability condition is guaranteed at the 1% significance level only in logarithmic first differences.

TABLE 1
Augmented Dickey-Fuller Tests for Unit Roots—Log Levels

	ADF Test Statistic	Coefficient (Std. Errors in parenthesis)
Total Non-Farm Employment	-9.551	-2.027*** (0.212)
Mexican IPI	-7.320	-1.910*** (0.261)
U.S. IPI	-4.480	-0.527*** (0.118)
Mexican Imports from U.S.	-7.621	-1.800*** (0.236)

[a] All variables entered the model in logarithms.
[b] Test statistics come from the equation:

$$\Delta y_t = \mu + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \cdots + \delta_{\rho-1} \Delta y_{t-\rho+1} + \varepsilon_t$$

where $\Delta y_t = y_t - y_{t-1}$, T denotes trend, μ and δ are parameters, and ε_t is assumed to be white noise. This is used to test:

$$H_0 : \gamma = 0\ ,\ H_1 : \gamma < 0$$

[c] MacKinnon (1991) provides critical values for rejection of hypotheses of a unit root. The null hypothesis of a unit root is rejected against the one-sided alternative if the t-statistic is less than (lies to the left of) the critical value. If the test fails to reject the null hypothesis of a unit root in the series at any of the reported significance levels, then the series is non-stationary.
[d] *, **, and *** means that the test rejects the null hypothesis of a unit root in the series at the 10%, 5%, and 1% significance levels, respectively. In this case, only Services, Total Government, and Mexican Imports from the U.S. are found to be stationary.

Table 2 reports the Johansen (1988) cointegration test for the four variables considered in the study. The results show that the variables are not cointegrated at the 5% or 1% levels of significance rendering the inclusion of the error correction term in the vector autogression model unnecessary.

Table 2
Johansen Cointegration Test[a]

	Likelihood Ratio	5 Percent Critical Value[b]	1 Percent Critical Value
Total Non-Farm Employment	46.47	47.21	54.46
Mexican IPI	19.95	29.68	35.65
U.S. IPI	6.73	15.41	20.04
Mexican Imports from U.S.	.10	3.76	6.65

[a] All variables entered the model in logarithms.
[b] Test statistics come from Johansen and Juselius (1990).

In a recent paper, Diebold (1998a) recounts that the initial interest in non-structural econometric models arose as a break from structural modeling because economists could not reach a consensus on the economy's true structure. Thus, a key advantage of non-structural models, such as a VAR model, is that they reveal important dynamic characteristics of the economy without having to impose structural restrictions from a particular economic theory. This explains the popularity that has accompanied Sims' (1980) seminal paper on vector autoregression (VAR) modeling. However, neither Diebold (1998a) nor Sims et al. (1991) foresee VAR modeling as substituting structural econometric models. Rather, they argue that vector autoregression (VAR) and structural econometric models have complementary roles in the modeling of macroeconomic time series.

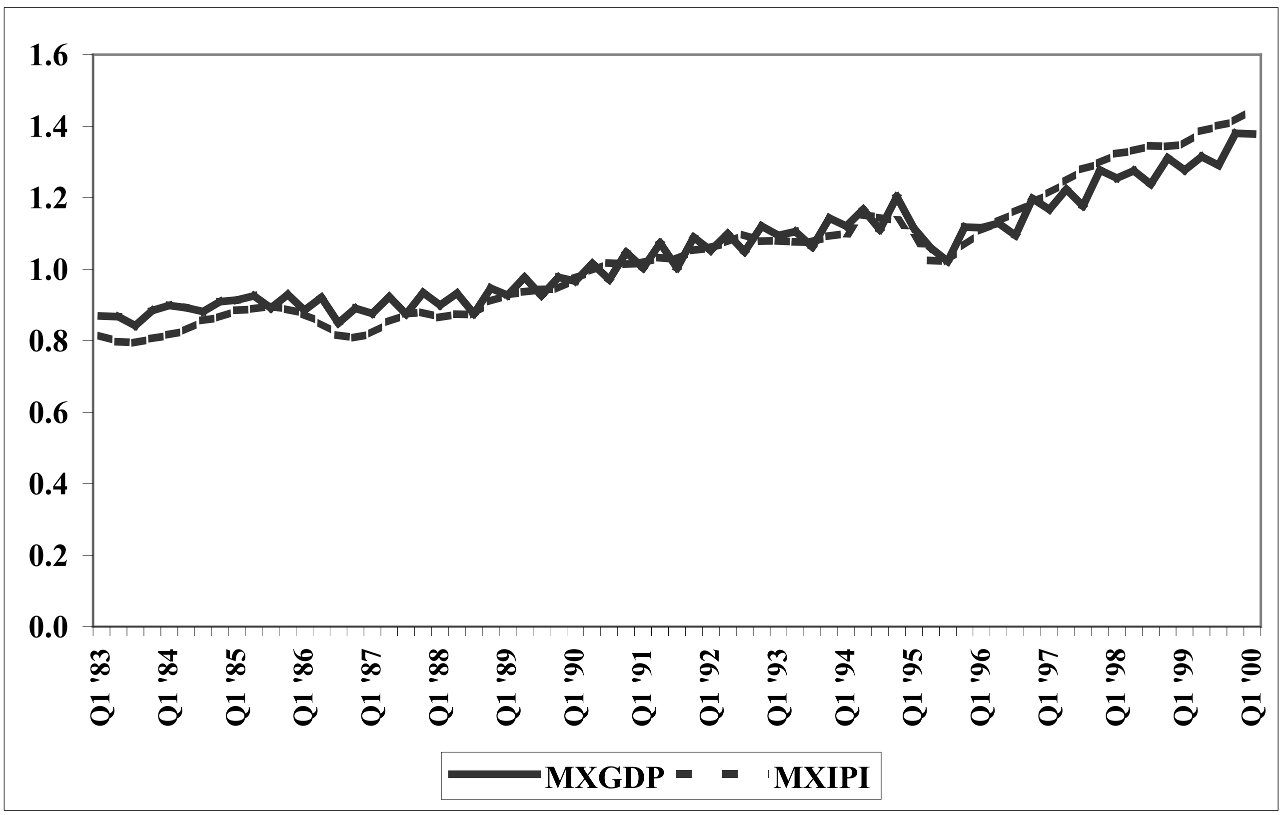
The VAR includes four endogenous variables: The U.S. industrial production index (USIP), Texas total non-farm employment (NFETX), Mexican imports from the U.S.

(MXMUS), and Mexican industrial production index (MXIP). Using the logarithmic first differences of the series the model can be expressed as,

$$P_t = \omega(B)P_t + \alpha Z_t + \varepsilon_t$$

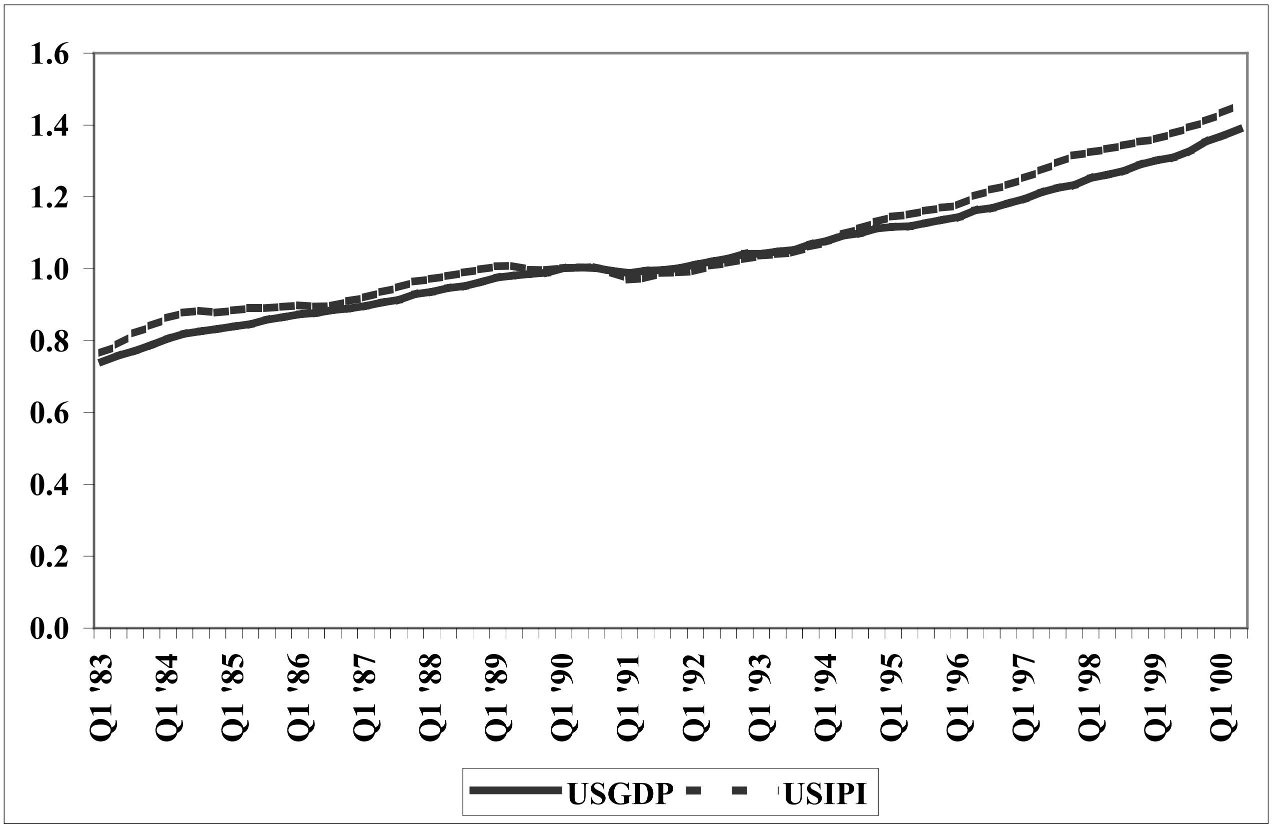
where P_t is comprised of the lags of the above mentioned variables, $\omega(B)$ is a matrix of polynomials in lag operator B, and ε_t is a vector of random error terms.

FIGURE 1
Industrial Production and Gross Domestic Product Indexes for Mexico
1983-2000



Source: Mexican Industrial Production (MXIPI) and Gross Domestic Product (MXGDP) Indexes are obtained from OECD databases as reported in DataStream. Base year is 1990 for both indexes.

FIGURE 2
Industrial Production and Gross Domestic Product Indexes for the United States
1983-2000



Source: The U.S. Industrial Production (USIPI) and Gross Domestic Product (USGDP) Indexes are obtained from OECD databases as reported in DataStream. Base year is 1990 for both indexes.

Despite the fact that the index of industrial production index does not take into account growth derived from the agricultural sector, which is an important sector for Mexico and the United States, they are nevertheless traditionally used as a proxy for GDP and economic growth because they have been shown to exhibit very similar growth trends. Figures 1 and 2 plot the close relationship between industrial production index and GDP for Mexico and the United States respectively. Thus, the monthly figures of the industrial production index are used as a proxy for the GDP data, which is reported quarterly.

IV. Empirical Results

From an empirical standpoint, the primary use of the VAR model is in impulse response analysis, variance decompositions, and Granger causality tests. The selection of the appropriate lag length is critical in the modeling process. For instance, small lag lengths result in misspecification of the system, while large lag lengths waste degrees of freedom (Enders, 1995).

A common procedure to test lag length is to estimate a vector autoregression model beginning with the longest reasonable lag length and testing to see whether it can be shortened to minimize the loss of degrees of freedom (Enders, 1995; Dickey et al., 1991). Based on the a priori perception that one year may be sufficient time to capture the system's dynamics, this analysis begins with a starting lag length of 12. Then, to determine if a reduced number of lags is appropriate, a second vector autoregression model is estimated over the same time period with 8 lags. The likelihood ratio test is used to determine whether the appropriate lag length is 12 or 8 lags. The results show that reducing the lag length from 12 to 8 months has a significant χ^2 value rejecting the null hypothesis of 8 in favor of the inclusion of 12 lags. Alternative test criteria to determine appropriate lag lengths are the multivariate generalizations of the Akaike Information Criterion (AIC) and the Schwartz-Bayesian Criterion (SBC). We conduct both tests to compare the results obtained from the likelihood ratio test. The calculated AIC and SBC criteria show mixed results. On one hand, the SBC confirms that the 8-lag model is the most appropriate. On the other hand, the AIC shows the 12-lag model to be the most appropriate. Based on the likelihood ratio and AIC tests, we have chosen to utilize the unrestricted model to better capture the dynamics of the data generating process.

Table 3 reports estimation results and diagnostic tests for the VAR model. The coefficient estimates appear to be insignificant for some variables. However, it is not surprising to obtain such results since in any VAR estimation, the regressors are likely to be highly collinear. Therefore, the t-tests on individual coefficients may not be reliable guides for paring down the model (Enders, 1995). Nevertheless, based on the t-tests, the U.S. industrial production index and Texas non-farm employment seems to be influenced by changes in its own lags. The Ljung-Box Q statistics reveal that the residuals from the regression are not serially correlated. Further, the residuals from the VAR estimations mostly appear to be conforming to the normality assumption.

TABLE 3
VAR REGRESSION COEFFICIENTS AND DIAGNOSTIC TESTS
(Standard errors in parentheses)

USIP			MXMUS			MXIP			NFETX		
	Est.	S.E.		Est.	S.E.		Est.	S.E.		Est.	S.E.
USIP1	0.063	0.083	USIP1	0.197	1.494	USIP1	0.354	0.490	USIP1*	0.096	0.053
USIP2	0.008	0.083	USIP2	-1.377	1.492	USIP2	-0.776	0.489	USIP2*	0.095	0.052
USIP3**	0.265	0.082	USIP3	-1.325	1.481	USIP3	0.183	0.486	USIP3	0.054	0.052
USIP4	0.072	0.084	USIP4	-2.359	1.513	USIP4	0.608	0.496	USIP4	0.017	0.053
USIP5	-0.025	0.082	USIP5**	3.409	1.486	USIP5*	0.945	0.487	USIP5	0.043	0.052
USIP6*	-0.141	0.082	USIP6	-1.124	1.480	USIP6	0.063	0.485	USIP6	0.029	0.052
USIP7	-0.055	0.081	USIP7	1.393	1.463	USIP7	-0.219	0.480	USIP7	0.069	0.051
USIP8**	0.188	0.081	USIP8	-1.763	1.461	USIP8	-0.277	0.479	USIP8	0.063	0.051
USIP9	0.122	0.081	USIP9	-0.205	1.463	USIP9	-0.304	0.480	USIP9	0.038	0.051
USIP10*	0.188	0.079	USIP10	-0.186	1.419	USIP10	0.168	0.465	USIP10	0.014	0.050
USIP11	-0.041	0.078	USIP11**	4.404	1.414	USIP11	0.579	0.463	USIP11	0.038	0.050
USIP12	-0.124	0.080	USIP12	0.028	1.450	USIP12	-0.281	0.476	USIP12	-0.014	0.051
MXMUS1	0.002	0.005	MXMUS1**	-0.288	0.093	MXMUS1	-0.003	0.030	MXMUS1*	0.005	0.003
MXMUS2*	-0.009	0.005	MXMUS2	-0.073	0.092	MXMUS2	-0.008	0.030	MXMUS2*	0.005	0.003
MXMUS3	-0.002	0.005	MXMUS3	0.079	0.092	MXMUS3	0.060	0.030	MXMUS3*	0.005	0.003

MXMUS4	0.003	0.005	MXMUS4	-0.011	0.087	MXMUS4	-0.020	0.029	MXMUS4	-0.002	0.003
MXMUS5	0.003	0.004	MXMUS5	0.103	0.080	MXMUS5	0.034	0.026	MXMUS5	0.001	0.003
MXMUS6	0.006	0.004	MXMUS6	-0.003	0.080	MXMUS6	0.032	0.026	MXMUS6	-0.002	0.003
MXMUS7	-0.001	0.004	MXMUS7	0.006	0.080	MXMUS7	0.020	0.026	MXMUS7	0.000	0.003
MXMUS8	0.005	0.004	MXMUS8	0.017	0.079	MXMUS8	-0.003	0.026	MXMUS8	0.001	0.003
MXMUS9	-0.005	0.004	MXMUS9	-0.126	0.076	MXMUS9	0.016	0.025	MXMUS9	0.002	0.003
MXMUS10	0.001	0.004	MXMUS10	-0.047	0.077	MXMUS10	0.007	0.025	MXMUS10	0.000	0.003
MXMUS11	-0.006	0.004	MXMUS11*	0.154	0.073	MXMUS11	0.008	0.024	MXMUS11	0.005	0.003
MXMUS12	0.004	0.004	MXMUS12	0.109	0.069	MXMUS12	-0.006	0.023	MXMUS12	0.000	0.002
MXIP1	0.007	0.016	MXIP1*	-0.455	0.288	MXIP1*	-0.524	0.094	MXIP1*	0.019	0.010
MXIP2*	0.037	0.017	MXIP2	0.059	0.317	MXIP2	-0.127	0.104	MXIP2	0.014	0.011
MXIP3	-0.022	0.018	MXIP3	0.421	0.325	MXIP3	0.025	0.106	MXIP3	-0.006	0.011
MXIP4	-0.021	0.018	MXIP4	0.227	0.325	MXIP4	0.120	0.106	MXIP4	0.012	0.011
MXIP5	-0.022	0.017	MXIP5	-0.074	0.315	MXIP5	-0.116	0.103	MXIP5	0.014	0.011
MXIP6	0.004	0.017	MXIP6	-0.211	0.310	MXIP6*	-0.208	0.102	MXIP6	0.010	0.011
MXIP7	0.026	0.017	MXIP7	-0.461	0.311	MXIP7*	-0.217	0.102	MXIP7	-0.003	0.011
MXIP8	0.001	0.017	MXIP8	0.074	0.316	MXIP8	-0.123	0.104	MXIP8	-0.009	0.011
MXIP9	-0.002	0.017	MXIP9	0.319	0.315	MXIP9	0.060	0.103	MXIP9	0.008	0.011
MXIP10	-0.025	0.017	MXIP10	-0.027	0.317	MXIP10	-0.139	0.104	MXIP10	-0.017	0.011
MXIP11	-0.009	0.017	MXIP11	0.095	0.315	MXIP11	-0.047	0.103	MXIP11	-0.007	0.011
MXIP12	-0.006	0.015	MXIP12	0.216	0.278	MXIP12	0.167	0.091	MXIP12	0.012	0.010
NFETX1	0.047	0.091	NFETX1	0.211	1.635	NFETX1*	1.749	0.536	NFETX1*	-0.093	0.057
NFETX2	0.042	0.095	NFETX2	-2.417	1.724	NFETX2*	-1.326	0.565	NFETX2	-0.029	0.061
NFETX3	-0.110	0.095	NFETX3	1.469	1.718	NFETX3	-0.048	0.563	NFETX3	0.034	0.060
NFETX4	0.064	0.093	NFETX4	0.216	1.682	NFETX4	-0.267	0.551	NFETX4	-0.005	0.059
NFETX5	-0.102	0.090	NFETX5	0.068	1.628	NFETX5	-0.574	0.534	NFETX5*	-0.094	0.057
NFETX6	0.026	0.091	NFETX6	0.668	1.643	NFETX6*	0.755	0.539	NFETX6**	0.157	0.058
NFETX7*	-0.230	0.091	NFETX7	-0.383	1.646	NFETX7	-0.724	0.540	NFETX7	-0.035	0.058
NFETX8	-0.114	0.093	NFETX8	1.377	1.675	NFETX8	0.945	0.549	NFETX8	-0.076	0.059
NFETX9	0.081	0.094	NFETX9*	-4.087	1.701	NFETX9	-0.924	0.558	NFETX9	-0.082	0.060
NFETX10	-0.064	0.093	NFETX10	-1.271	1.685	NFETX10	-0.524	0.553	NFETX10	-0.070	0.059
NFETX11	0.102	0.087	NFETX11	-0.001	1.566	NFETX11*	1.654	0.514	NFETX11	0.004	0.055
NFETX12	-0.084	0.087	NFETX12*	2.536	1.573	NFETX12	0.349	0.516	NFETX12*	0.700	0.055
C*	0.200	0.073	C	1.611	1.327	C	-0.058	0.435	C*	-0.082	0.047
Adj. R-sq.	0.044		Adj. R-sq.	0.327		Adj. R-sq.	0.542		Adj. R-sq.	0.821	
SSR	33.864		SSR	10923.620		SSR	1174.090		SSR	13.506	
SEE	0.484		SEE	8.710		SEE	2.855		SEE	0.306	
AIC	1.605		AIC	7.382		AIC	5.151		AIC	0.686	
Schwarz	2.433		Schwarz	8.210		Schwarz	5.980		Schwarz	1.514	
S.D. dep.	0.495		S.D. dep.	10.613		S.D. dep.	4.217		S.D. dep.	0.724	
Ljung-Box	0.816		Ljung-Box	0.991		Ljung-Box	0.886		Ljung-Box	0.306	
Jarque-Bera	0.741		Jarque-Bera	0.001		Jarque-Bera	0.405		Jarque-Bera	0.428	

*, ** represent significance levels at 5% and 1% respectively. The Jarque-Bera, and Ljung-Box statistics indicate p-values. For the Ljung-Box Q statistic, the p-value is reported for the first lag, which continues to remain insignificant for the remaining lags

We plot the conventional impulse response functions to assess the relative importance of various shocks in explaining other variables in the VAR model. These graphs allow us to trace the response of one variable resulting from a once and for all shock to another variable in the system. If the innovations in the error terms are contemporaneously uncorrelated, interpretation of the impulse response is straightforward. If however, the innovations are contemporaneously correlated, after Cholesky decomposition, the impulse response functions estimations may not be reliable (Enders, 1995). To test for this possibility we re-estimate the model with different orderings of the variables and find that the results are not sensitive to the way the variables are ordered in the system. Moreover, using the Monte Carlo method confidence bands can be constructed around the mean response to determine whether the impulse responses are statistically significant. If the upper and lower response carry the same sign as the mean response, the response becomes statistically significant at the 5% significance level.

Figure 3 plots the response of the Total non-farm employment in Texas to a one-time shock in the U.S. Industrial Production Index. A one-time shock to the U.S. industrial production index produces an immediate and statistically significant response of Texas non-farm employment, which lasts for three months thereafter becoming insignificant in the following months. Such a response pattern is consistent with the view that the U.S. industrial production index is the most important determinant of Texas non-farm employment in the model.

Figure 4 plots the response of Texas non-farm employment to a one-time shock to the imports of Mexico from the U.S. Texas non-farm employment responds significantly in the second month after a lag of one month. The response pattern is different from figure 3 where the response occurs immediately and stays sustained for three months. Thus such a response pattern is consistent with the view that the Texas non-farm employment is impacted significantly by the imports of Mexico from the U.S. but not as strong as the influence of the U.S. industrial production index on Texas non-farm employment.

Figure 3
Response of Texas total non-farm employment to U.S. industrial production index

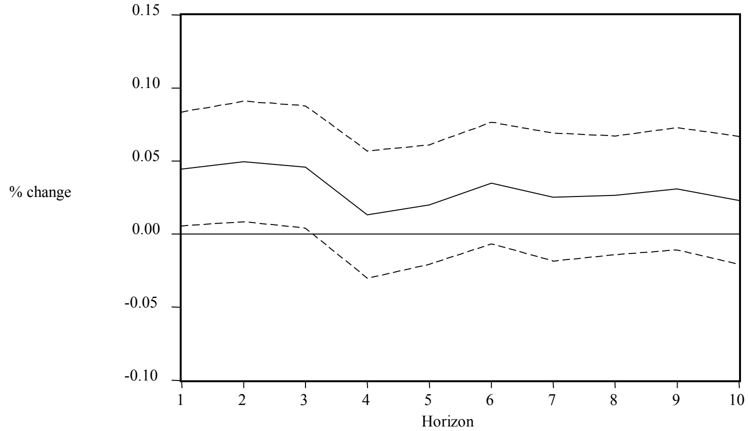


Figure 4
Response of Texas non-farm employment to imports of Mexico from the U.S.

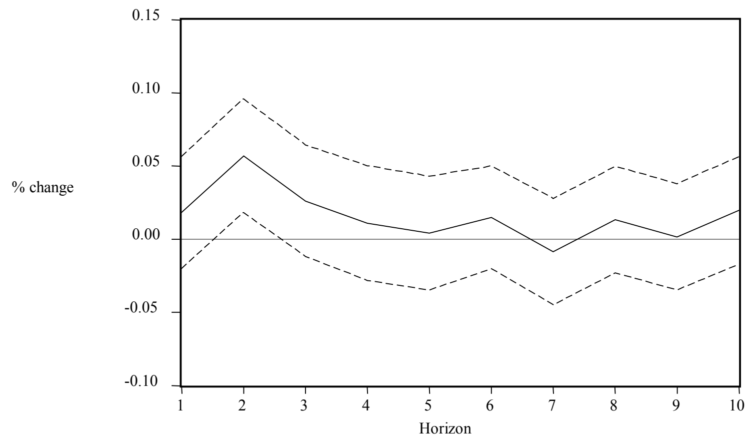


Figure 5
Response of Texas non-farm employment to the industrial production index of Mexio

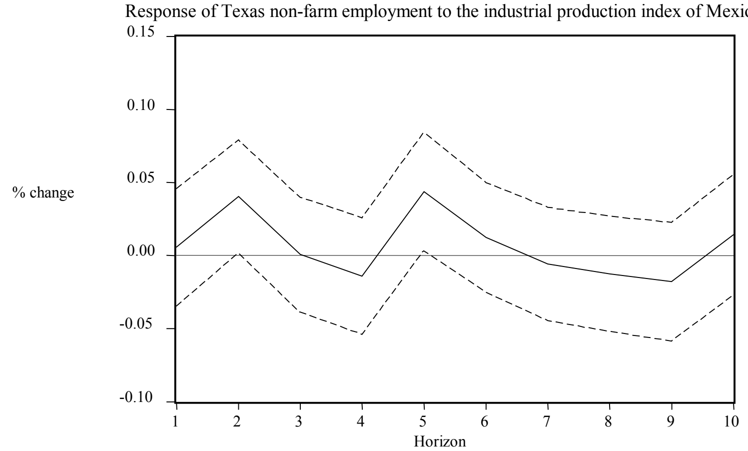


Figure 5 plots the response of Texas non-farm employment to a one-time shock to Mexican industrial production index. Similar to response pattern in Figure-4, Texas non-farm employment response is again statistically significant in the second and fifth month after a lag in the first month. However, the magnitude of the response is lower than the response plotted in Figure 3 and 4 suggesting that the industrial production index of Mexico is a significant determinant of Texas non-farm employment but not to the extent of the U.S. industrial production index and Mexican imports from the U.S. in the model.

V. Concluding Remarks

In this paper, we investigate whether regional employment figures from Texas are impacted by the national key economic variables from Mexico and the U.S. by constructing a four variable vector autoregression (VAR) model. We postulate that changes in Mexico's industrial production index and imports of Mexico from the U.S. may be an important factor predicting changes in aggregate Texas employment. The most important determinant of Texas non-farm employment is found to be the U.S. industrial production index in the model. However, we find results consistent with the view that movements in Mexico's industrial production index and Mexican imports from the U.S. play an important role in shaping that Texas non-farm employment figures. Thus, incorporating information related to Mexican economy may assist local policy makers in anticipating and adapting to business cycle-related fluctuations in critical sectors of the local economy. Given the general results obtained in this analysis, an interesting variation on the theme for future research would be to investigate whether changes in the Mexican economy affect the composition of Texas employment rather than its aggregate level.

References

Carlina, G. and Robert DeFina. 1999. "The Differential Regional Effects of Monetary Policy: Evidence from the U.S. States," *Journal of Regional Science*, 39(2), pp. 339-358.

Casario, Michelle. 1996. "North American Free Trade Agreement Bilateral Trade Effects." *Contemporary Economic Policy,* vol. XIV, January, pp. 36-47.

Crane, Steven E. and Farrokh Nourzad. 1998. "Improving local manufacturing employment forecasts using cointegration analysis." *Growth & Change* 29(2), Spring, pp. 175-195.

Dávila, Alberto and Marie T. Mora. 1997. "English Skill, Earnings, and the Occupational Sorting of Mexican American Men Working along the U.S.-Mexico Border." University of Texas-Pan American and New Mexico State University Working Paper.

Dickey, David A., Dennis W. Jansen, and Daniel L. Thornton. 1991. "A Primer on Cointegration with an Application to Money and Income." *Federal Reserve Bank of St. Louis Review* 73(2), March/April, pp. 58-78.

Diebold, Francis X. 1998a. "The Past, Present, and Future of Macroeconomic Forecasting." *Journal of Economic Perspectives* 12(2), spring, pp. 175-192.

Diebold, Francis X. 1998b. *Elements of Forecasting*. Cincinnati, OH: South-Western College Publishing.

Doan, Thomas A. 1997, *Regression Analysis of Time Series,* VAR Econometrics, Evanston, IL.

Enders, Walter. 1995. *Applied Econometric Time Series*. New York: John Wiley & Sons, Inc.

Fanchon, Phillip and Jeanne Wendel. 1992. "Estimating VAR Models under Non-Stationarity and Cointegration: Alternative Approaches for Forecasting Cattle Prices." *Applied Economics* 24(2), February, pp. 207-217.

Johansen, S. 1988. "Statistical Analysis of Cointegration Vectors," *Journal of Economic Dynamics and Control*, 12: 231-54.

Johansen, S. and K. Juselius. 1990. "Maximum Likelihood Estimation and Inference on Cointegration: With Applications to the Demand for Money," *Oxford Bulleting of Economics and Finance*, 2(2): 181-93.

MacKinnon, J.G. 1991. "Critical Values for Cointegration Tests, " in R. F. Engle and C.W. J. Granger (eds), *Long-Run Economic Relationships*, Oxford University Press, Oxford.

Naka, Atsuyuki and David Tufte. 1997. "Examining impulse response functions in cointegrated systems." *Applied Economics* 29(12), December, pp. 1593-1603.

Sims, Christopher A. 1980. "Macroeconomics and Reality." *Econometrica* 48: 1-48.

Sims, Christopher A. 1988. "Bayesian Skepticism on Unit Root Econometrics." *Journal of Economic Dynamics & Control* 12(2,3): 463-474. Jun/Sep.

Sims, Christopher A., Clements, Michael P. Mizon, Grayham. Kirchgassner, Gebhard. 1991. "Empirical Analysis of Macroeconomic Time Series: VAR and Structural Models; Comments." *European Economic Review* 35(4): 887-932. May.

Endnotes

1 Here, we make use of the fact that employment corresponding to AE must equal to the employment corresponding to Real GDP at the equilibrium point.
2 Other key economic indicators have produced similar or insignificant results to the ones reported in this study.