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MAQUILADORA EMPLOYMENT DYNAMICS IN CHIHUAHUA CITY, MEXICO

Thomas M. Fullerton, Jr.
University of Texas at El Paso, USA
Luis Bernardo Torres Ruiz
Banco de México, Mexico and University of Colorado, USA

ABSTRACT

As exports from regions of developing economies to higher income economies grow, business cycle linkages between these areas also increase. This study applies a transfer function ARIMA methodology to the analysis of maquiladora sector employment in a non-border region of Mexico as a means for measuring its international business cycles linkages to the export market in the United States. Statistically significant payroll responses are found in response to variations in the exchange rate, domestic wage levels, foreign investment, and United States industrial production. Simulation testing is also completed as an additional means of model reliability verification. Because data requirements are not excessive, replication for other developing country markets is feasible.

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INTRODUCTION

The Mexican in-bond assembly industry, also known as the maquiladora industry, has spread to interior regions of the country. It is now an important source of direct foreign investment and employment in non-border areas. Consequently, these portions of Mexico are no longer isolated from the effects of business cycle fluctuations in the United States. Measurement of these trends and linkages represents an important task for understanding the behavior of these economies. It also provides a template for one means of monitoring the impacts of globalization on developing economies, many of whom are exporting larger volumes of merchandise to higher income regions such as North America or the European Union.

This paper replicates and extends an earlier study (Fullerton and Schauer, 2001) that examines short-run maquiladora dynamics for a large border city. To date there have been very few research efforts that examine short-run employment trends in the maquiladora industry. Even fewer of these efforts have dealt with non-border labor markets. A contributing factor is limited availability of time series data for non-border regions. The latter circumstance is partially due to the fact that maquiladoras initially did not invest very many resources in labor markets in the interior of Mexico.

The data constraint is less binding for Chihuahua City, an urban economy where the maquiladora industry has operated for more then twenty years. During the last two and a half decades, in-bond assembly manufacturing has expanded at a steady pace. The sector now accounts for approximately 27 percent of all formal sector jobs where the latter are defined as those covered by the social security system in Mexico. Given these characteristics, the city of Chihuahua is a natural candidate for short-term maquiladora employment analysis and modeling.

Subsequent material in the paper includes a short overview of relevant maquiladora and time series econometric research in the next section. The third section summarizes the data and the methodology utilized. Empirical results are discussed in the fourth section. The final section presents conclusions as well as suggestions for future research.

LITERATURE REVIEW

The Border Industrialization Program was enacted in 1965 by the Mexican government in a successful attempt to reduce unemployment rates in communities along the border following the abolition of the Bracero farm labor program by the United States (Ayer and Layton, 1974). Among the policies used to induce manufacturers to invest along the border in Mexico subsequent to 1965 are duty free import of plant machinery, raw materials, and intermediate inputs; relatively low transportation costs; and inexpensive labor. In the United States, duties are imposed only on the value added (principally labor costs and overhead) of the production that takes place in Mexico.

In general terms, a maquiladora is a factory that assembles imported components into products for export. Its ownership may be foreign or domestic (Guajardo, 1990). Recent in-bond manufacturing studies have examined numerous topics including regional integration (Hanson, 2001) and industrial development (Mendoza Cota, 2002). Results in those studies point to a variety of impacts associated with regional agglomeration effects. Aggregate employment effects have also been examined in cross-border contexts for maquiladoras (Gruben, 1990; Silver and Pavlakovich, 1994; Fullerton, 2001). In an early effort, Ayer and Layton (1974) estimates twin plant impacts on U.S. employment and population resulting from cross-border expenditures by Mexican employees. Simulations with an input-output model underscore positive linkages between jobs and population on the United States side of the border.

Several papers analyze regional outcomes associated with payroll fluctuations in this industry. Cobb, Molina and Sokulsky (1989) analyze the impact of in-bond assembly expansion on commuter flows at six international ports-of-entry in Texas for the 1975-1985 period. Dávila (1990) documents the interplay of currency valuation and direct foreign investment in northern Mexico. More recently, Gruben and Kiser (2001) conclude that international wage ratios and the growth rate of United States industrial output will remain the most important causal factors behind future maquiladora expansion throughout the country.

Fullerton and Schauer (2001) employ traditional transfer function ARIMA time series analysis to study maquiladora payroll fluctuations in Ciudad Juárez. Similar to some of the previously cited work, the influence of United States business fluctuations, real wages, and exchange movements are confirmed for this large metropolitan economy. The filter-oriented transfer function methodology (Box and Jenkins, 1976) is also utilized in separate border area studies that gauge the impacts of maquiladora activity in Ciudad Juárez on international bridge crossings and private sector electricity consumption patterns (Fullerton, 1998; 2000). Results obtained in these transfer ARIMA studies have not previously been replicated in other geographic markets such as Chihuahua City.

An alternative dynamic modeling approach is provided by the linear transfer function (LTF) approach to time series analysis (Liu and Hanssens, 1982; Pankratz, 1991). The principal difference between the traditional transfer ARIMA and the LTF methodologies arises in the identification procedure. Because it first examines potential correlations between input series and dependent variable, the LTF procedure places stronger emphasis on modeling linkages between the regressors and the left-hand-side variable than does traditional transfer analysis. Trívez and Mur (1999) successfully employ the LTF approach to predict employment patterns in the Aragon region of Spain. The LTF methodology has also been applied to international energy and water markets (Liu and Lin, 1991; Tserkezos, 1992; Fullerton and Nava, 2003).

To date, very few time series studies of regional maquiladora labor markets in Mexico have been completed. LTF modeling analysis offers a fairly direct means for modeling the local, regional, and international forces that come to bear on in-bond assembly operations. Because of the ease with which it handles multiple time series linkages and lag structures, this ARIMA tool may prove helpful in analyzing cyclical fluctuations such as those that affect labor market conditions in the Chihuahua City metropolitan economy. Given its relative parsimony and minimal data requirements, it is also appealing from the perspective of analyzing urban economies in developing areas where data are not as readily obtained they are in higher income regions.

DATA AND METHODOLOGY

The city of Chihuahua is home to one of the most important concentrations of in-bond assembly activities in Mexico. Monthly maquiladora employment data for Chihuahua City are available from the Instituto Nacional de Estadística, Geografía, e Informática (INEGI) web site (www.inegi.gob.mx). The January 1987 – December 2001 sample period includes three large-scale peso devaluations (1982, 1986, 1994). Other INEGI data series utilized include an inflation adjusted wage and salaries index and the number of in-bond assembly plants in operation in the city of Chihuahua. The latter variable is used as a scale proxy for direct foreign investment in this regional industry segment. Because some maquiladora series are not available in print form prior to 1990, INEGI archivists in Aguas Calientes were contacted in order to obtain reliable estimates for the January 1987 – December 1989 sub-sample period.

Historically, most maquiladora output is exported to parent companies located north of the border in the United States (Fuentes, 1989; Montemayor, 1992). Consequently, business cycle fluctuations in the northern industrial economy generate sizable impacts on the maquiladora industry in Mexico. To capture that impact, several Federal Reserve System Board of Governors United States industrial production indices are used as proxies for overall market conditions (www.federalreserve.gov). They include the national index plus four basic market groups: automotive products, appliances and home computing equipment, audio and video equipment, and clothing. The latter series are utilized to distinguish between the effects of different industries, since business conditions frequently differ from sector to sector and lead to differential effects on regional maquiladora market activities. A real peso/dollar exchange rate index calculated by the Federal Reserve Bank of Dallas (www.dallasfed.org) is also included to allow for potentially heterogeneous reactions by international investment to distinct labor and currency market developments that individually affect dollar-denominated wage measures (Fullerton, Sawyer, and Sprinkle, 1999).

To help identify potential lag structures that exist between in-bond assembly payrolls in Chihuahua City and the various independent variable candidates, cross correlation functions (CCFs) are estimated for stationary components of the data (Mills, 1990). First moment stationarity is assessed via chi-square Q-statistics calculated from individual series autocorrelation functions (ACFs). Under the LTF procedure, the transfer function portions of the equation are analyzed first. Remaining non-random variations in the dependent variable are then removed by introducing autoregressive and moving average parameters to the model (Liu and Hanssens, 1982; McGinnis, 1994). To investigate the potential dynamic relationship between the stationary component of the maquiladora employment dependent variable *m* and an arbitrary stationary independent variable *x* at lag *k*, CCFs are estimated as follows (Wei, 1990):

$$\hat{r}_{xw}(k) = \frac{\sum_{t=1}^{T-k}(x_t - \bar{x})(m_{t+k} - \overline{m})}{\hat{\sigma}_x \hat{\sigma}_m}, \text{ for k = 0,1,2,…, and t = 1,2,…,T.} \quad (1)$$

Table 1 describes the variables included in the analysis. General transfer ARIMA functional formats proposed for modeling short-term maquiladora employment movements in the city of Chihuahua are as follows:

$$\mathrm{CHMQ}_t = \theta_0 + \sum_{i=1}^{p} \phi_i \mathrm{CHMQ}_{t-i} + \sum_{j=1}^{q} \theta_j u_{t-j} + \sum_{k=1}^{K} a_k \mathrm{WAGE}_{t-k} + \sum_{m=1}^{M} b_m \mathrm{REX}_{t-m} + \sum_{z=1}^{Z} c_s \mathrm{PLANT}_{t-s} + \sum_{s=1}^{S} d_s \mathrm{IND}_{t-s} + u_t , \quad (2)$$

$$\mathrm{CHMQ}_t = \theta_0 + \sum_{i=1}^{p} \phi_i \mathrm{CHMQ}_{t-i} + \sum_{j=1}^{q} \theta_j v_{t-j} + \sum_{k=1}^{K} a_k \mathrm{WAGE}_{t-k} + \sum_{m=1}^{M} b_m \mathrm{REX}_{t-m} + \sum_{z=1}^{Z} c_s \mathrm{PLANT}_{t-s} + \sum_{g=1}^{G} d_g \mathrm{AUTO}_{t-g} + \sum_{l=1}^{L} f_l \mathrm{VIDEO}_{t-l} + \sum_{r=1}^{R} h_r \mathrm{CLOTH}_{t-r} + v_t , \quad (3)$$

Hypothesized relationships between the dependent and independent variables in Equations 1 and 2 are negative for real wages, and positive for the real exchange rate, factory, and industrial activity variables. Time lags are permitted to vary for the autoregressive and moving average parameters of the output variables as well as for each of the regressor series.

Once parameter estimation has been completed for each equation, the resulting models are subjected to an additional round of diagnostic checking that involves comparing out-of-sample simulation accuracies. Such a step is often useful in terms of overall model evaluation and assessment (Leamer, 1983; Granger, 1996; McCloskey and Ziliak, 1996). Static simulations are conducted over sample sub-periods that do not include data used to estimate model coefficients. The results are then used to calculate root-mean-square error (RMSE) statistics and Theil inequality coefficients (Pindyck and Rubinfeld, 1998). Those outcomes are assessed relative to univariate ARIMA and random walk benchmarks. Calculating multiple comparison criteria is a generally useful step. Taylor (1982) demonstrates the difficulty of forecast accuracy evaluation for various methodologies based on single accuracy determinants.

Initial estimation periods for the transfer and univariate ARIMA equations are from January 1987 through December 1998. The corresponding forecast period is from January 1999 to December 1999. The sample is then extended by one month for parameter estimation and rolled forward by one month for simulation. Accordingly, the second simulation period is from February 1999 to January 2000 and utilizes the equation that relies upon data from January 1987 through January 1999. The procedure generates 36 separate estimation and 12-step ahead forecast sequences. Simulation results for all three approaches are then segregated by step-length. That gives rise to 36 one-month

Table 1: Variable Names

Variable	Description
CHMQ	Monthly maquiladora employment in Chihuahua City
WAGE	Real wage per worker in pesos, 1985 = 100
REX	Real exchange rate, pesos per dollar, 2000 = 100
PLANT	Maquiladora factories in operation in Ciudad Chihuahua
IND	United States industrial production index, 1992 = 100
AUTO	United States automotive industrial production index, 1992 = 100
VIDEO	United States home appliance industrial production index, 1992 = 100
CLOTH	United States clothing apparel industrial production index, 1992 = 100

ahead forecasts, 35 two-month ahead forecasts, 34 three-month ahead forecasts, and so on to 25 twelve-month ahead forecasts.

Prediction errors are used to calculate root mean square error (RMSE) values for all 12-month step-lengths as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(m_t^s - m_t^a)^2} \tag{4}$$

where m_t^s is the forecast value for CHMQ_t , m_t^a is the actual value for CHMQ_t , and T is the number of simulation observations for each step-length.

RMSE statistics are bounded from below by zero, but have no upper limit. Because this makes that class of accuracy metric somewhat difficult to interpret, Theil inequality coefficients are also computed for each set of forecasts (Pindyck and Rubinfeld, 1998). They are calculated as shown in Equation 5:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(m_t^s - m_t^a)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(m_t^s)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(m_t^a)^2}} \tag{5}$$

To gauge the nature of any simulation errors that occur, inequality proportions are calculated using second moments of the prediction errors (Theil, 1961):

$$U^M = \frac{(\overline{m}^s - \overline{m}^a)^2}{(1/T)\sum (m_t^s - m_t^a)^2} ,$$

$$U^S = \frac{(\sigma_s - \sigma_a)^2}{(1/T)\sum (m_t^s - m_t^a)^2} ,$$

and

$$U^C = \frac{2(1-\rho)\sigma_s\sigma_a}{(1/T)\sum (m_t^s - m_t^a)^2} . \tag{6}$$

The Theil inequality proportions are designed to measure forecast bias (U^M), variance (U^S), and covariance (U^C) proportions. The bias proportion is an indication of systematic error; the variance proportion indicates the ability of the model to replicate the degree of variability in the variable of interest; and the covariance proportion measures unsystematic error. Consequently, for any value U>0, the ideal distribution of inequality over the three sources is $U^M = U^S = 0$ and $U^C = 1$ (Theil, 1961; Pindyck and Rubinfeld, 1998). Small-sample properties of mean squared error statistics are generally unknown and forecast errors are usually serially correlated. Mizrach (1992) shows that this prevents U-coefficients from being subjected to formal inference tests. While formal testing is not feasible, West (1996) still shows RMSE and related metrics work reliably for forecast evaluation purposes.

Modified Theil inequality coefficients are also calculated as the ratio of the linear transfer functions RMSE´s to those associated with the univariate ARIMA and random walk procedures (Webb, 1984). If a modified Theil inequality coefficient is greater than 1, this implies that the univariate ARIMA, or the random walk, benchmark generates smaller absolute forecast errors than does the linear transfer function model. Conversely, if the modified Theil inequality coefficient is less than 1, this implies that the linear transfer function model generates smaller simulation errors than does the benchmark alternative. Both benchmark procedures have been shown to provide stiff competition to more data intensive constructs such as the LTF ARIMA equations estimated below (Nelson, 1984; Ashley, 1988).

EMPIRICAL RESULTS

Table 2 reports the LTF ARIMA estimation results that utilize the aggregate industrial production index for the United States. All of the series are differenced prior to estimation. Similar to the results obtained for Ciudad Juárez by Fullerton and Schauer (2001), all of the regressor series are found to impact maquiladora employment in the city of Chihuahua within periods of 12 months or less. All of the coefficients carry the hypothesized algebraic signs. With the exception of the intercept, all of parameter estimate computed t-statistics are significant at the 5-percent level.

Table 2: Aggregate U.S. Industrial Production Index LTF ARIMA Model

Variable	Coefficient	Std. Error	t-Statistic	Probability
Constant	29.8212	150.932	0.1976	0.8436
WAGE(-7)	-21.4384	8.37194	-2.5607	0.0115
WAGE(-8)	-24.2933	9.91793	-2.4494	0.0155
REX(-6)	55.7955	24.3240	2.2938	0.0232
REX(-9)	50.6926	22.6275	2.2403	0.0266
REX(-11)	76.0039	21.9509	3.4625	0.0007
PLANT(-3)	140.955	59.1121	2.3845	0.0184
PLANT(-12)	165.882	58.2254	2.8490	0.0050
IND(-2)	171.972	45.1963	3.8050	0.0002
AR(10)	0.28484	0.08633	3.2993	0.0012
R-squared	0.265998	Akaike info. criterion		17.2866
Adjusted R-squared	0.221059	Schwarz criterion		17.4813
Pseudo R-squared	0.973184	F-statistic		5.91911
S.E. of regression	1330.873	Prob(F-statistic)		0.00000
Sum squared residuals	2.6.E+08	Q(24)		25.4002
Log likelihood	-1347.001	Probability (Q-statistic)		0.32998
Durbin-Watson stat	2.142400	Iterations to convergence		8
Mean dependent variable	68.38854	Observations		157
Std. dvn. dep. variable	1507.941			

Sample Period: January 1987- December 2001.
Regressor lag lengths are in parentheses.

Because the data have been differenced prior to estimation, the coefficient of determination for the dependent variable used in modeling is fairly low, $R^2 = 0.265998$. However, adjusting he fitted data back to level form allows calculating a pseudo coefficient of determination. This measure indicates that the model explains approximately 97 percent of the variation in city of Chihuahua maquiladora employment levels over the sample period in question. Because the Q-statistic statistic for residual white noise is low, the equation specification does not overlook or fail to account for any systematic movement in the dependent variable. The other goodness of fit statistics in Table 2 also point to satisfactory model performance.

As expected for a labor demand equation, real wages exercise a strong influence on jobs in the in-bond manufacturing sector in Ciudad Chihuahua with coefficients estimated at lags 7 and 8. Inflation adjusted exchange rate coefficients are estimated at lags 6, 9 and ll. The longer period reaction time potentially reflects the erratic nature short-term currency movements. Given the different lag structures associated with the wage and exchange rate variables, it appears advisable to allow for potentially heterogeneous employment responses to changes in these variables even though both affect the international cost of doing business in Mexico. Similarly variant reaction patterns have also been uncovered in Latin American trade flow studies (Fullerton, Sawyer, and Sprinkle, 1999).

Direct foreign investment, proxied by the number factories in operation, also exercises strong effects on maquiladora sector payrolls in the city of Chihuahua. Two different plant coefficients appear in Table 2, one at lag 3 and the other at lag 12. Variations in United States industrial activity translate into in-bond assembly job impacts within a short 60-day period. The effect is obviously quick, possibly as a consequence of just-in-time inventory management practices and greater integration of the two national economies.

Table 3 summarizes the final specification and econometric results for the LTF ARIMA equation that uses disaggregated United States industrial production index components. Once again, all of the independent variables are found to impact maquiladora employment within periods of 12 months or less. Although the lag structure and transfer specification differs slightly from that shown in Table 2, all of the coefficients in Table 3 carry the hypothesized algebraic signs. Computed t-statistics are significant at the 5-percent level for all of the parameters other than those for the intercept term and automobile and parts sub-index. Significant automotive sector investments in metropolitan Chihuahua date from the early 1990s. Its relatively short history probably contributes to the relatively large magnitude observed for that estimated coefficient's standard deviation.

Table 3: Disaggregated U.S. Industrial Production Index LTF ARIMA Model

Variable	Coefficient	Std. Error	t-Statistic	Probability
Constant	27.2631	137.902	0.1977	0.8436
WAGE(-7)	-19.6586	7.69520	-2.5547	0.0116
REX(-11)	88.3983	22.2517	3.9727	0.0001
PLANT(-3)	130.652	61.0291	2.1408	0.0339
PLANT(-12)	162.696	59.8955	2.7163	0.0074
AUTO(-2)	10.1276	7.24771	1.3974	0.1644
VIDEO(-2)	19.4964	9.14555	2.1318	0.0347
CLOTH(-1)	79.0963	36.5339	2.1650	0.0320
AR(10)	0.21082	0.08137	2.5909	0.0105

R-squared	0.253120	Akaike info. criterion	17.29129
Adjusted R-squared	0.212750	Schwarz criterion	17.46648
Pseudo R-squared	0.975105	F-statistic	6.269769
S.E. of regression	1337.952	Prob(F-statistic)	0.000001
Sum squared residuals	2.7E+08	Q(24)	16.80600
Log likelihood	-1348.370	Probability (Q-statistic)	0.818665
Durbin-Watson stat	2.100010	Iterations to convergence	7
Mean dependent variable	68.38854	Observations	157
Std. dvn. dep. variable	1507.941		

Sample Period: January 1987- December 2001.
Regressor lag lengths are in parentheses.

The pseudo coefficient of determination indicates that the second equation also accounts for just over 97 percent of the variation in the dependent variable during the sample period in question. The other goodness-of-fit statistics in Table 3 also indicate that model estimation performance is acceptable. In contrast to the aggregate index model, only one real wage lag and one real exchange rate lag are included in the second equation. The respective reaction times of 7 months and 11 months for these variables are similar, however, to those reported in Table 2. Direct foreign investment is again found to lead to higher numbers of maquiladora jobs in Chihuahua City. Factory coefficients in Table 3 appear at lags 3 and 12, implying that in-bond assembly companies build to capacity over a period of time. A similar delay is also reported for Ciudad Juárez in the northern part of the state (Fullerton and Schauer, 2001).

As with the overall industrial production index, variations in the disaggregated sector components affect employment within 60-day periods. Slope coefficients are estimated at 2-month lags for the automotive parts, appliances, home computing, video, and audio equipment variables. The clothing index exhibits the fastest reaction time, one month. As noted above, the short lags potentially reflect just-in-time inventory management practices and greater economic integration between Mexico and the United States. While encouraging, good statistical estimation traits do not guarantee model simulation reliability (Leamer, 1983; Granger, 1996; McCloskey and Ziliak, 1996). To evaluate the out-of-sample forecast accuracy of each specification, Theil inequality coefficients are calculated for 12 individual step lengths. The scaling of the inequality statistic is between 0 and 1. Coefficient values close to 0 indicate that the predictive performance of the model is good, while values close to 1 lead to the opposite conclusion (Pindyck and Rubinfeld, 1998).

Additional accuracy assessment information is also obtained from examining simulation error second moments via Theil inequality coefficient bias, variance, and covariance proportions. The bias coefficient provides an indication of systematic simulation error and the variance proportion reflects the success of the model in replicating the variability of the dependent variable. Finally, the covariance proportion is a measure of unavoidable random errors. It is less worrisome since predicted outcomes are not expected to be perfectly correlated with actual values. For any value greater then zero for the Theil coefficient, the ideal distribution of the inequality components is zero for the bias and the variance proportions, and one for the covariance proportion (Pindyck and Rubinfeld, 1998).

Theil inequality results for the aggregate industrial production index LTF ARIMA function are presented in Table 4. For none of the 12-step lengths are U-values obtained that exceed than 0.07. This suggests that the predictive performance of the model is good. The U-statistic second moment covariance proportions exceed 0.75 across all forecast periods, further indicating that the model using the aggregate measure of industrial activity in the primary maquiladora export market is well specified.

Theil inequality coefficients for the disaggregated industrial production index equation appear in Table 5. The U-statistics for all of the step-lengths simulated are less than 0.07. Those outcomes indicate that the predictive performance of the disaggregated index model is also fairly accurate. The distribution of the inequality proportions is similarly encouraging. Bias and variance proportions are close to zero, while that for the covariance proportion never falls below 0.66.

Table 4: Aggregate U.S. Industrial Production Index LTF Simulation Results

	Theil-U	**U^m**	**U^s**	**U^c**	**Observations**
1-Month Ahead	0.014	0.007	0.002	0.991	36
2-Months Ahead	0.021	0.013	0.003	0.984	35
3- Months Ahead	0.027	0.018	0.003	0.979	34
4-Months Ahead	0.031	0.030	0.011	0.959	33
5-Months Ahead	0.034	0.056	0.030	0.914	32
6-Months Ahead	0.038	0.080	0.061	0.859	31
7-Months Ahead	0.043	0.093	0.082	0.825	30
8-Months Ahead	0.048	0.103	0.092	0.805	29
9-Months Ahead	0.053	0.104	0.086	0.811	28
10-Months Ahead	0.057	0.119	0.094	0.787	27
11-Months Ahead	0.061	0.132	0.097	0.771	26
12-Months Ahead	0.065	0.114	0.088	0.767	25

Table 5: Disaggregated U.S. Industrial Production Index LTF Simulation Results

	Theil-U	**U^m**	**U^s**	**U^c**	**Observations**
1-Month Ahead	0.014	0.014	0.000	0.986	36
2-Months Ahead	0.021	0.024	0.002	0.974	35
3- Months Ahead	0.027	0.027	0.003	0.970	34
4-Months Ahead	0.032	0.043	0.009	0.948	33
5-Months Ahead	0.035	0.075	0.024	0.901	32
6-Months Ahead	0.039	0.107	0.047	0.846	31
7-Months Ahead	0.044	0.133	0.078	0.789	30
8-Months Ahead	0.049	0.150	0.103	0.747	29
9-Months Ahead	0.053	0.153	0.117	0.730	28
10-Months Ahead	0.056	0.174	0.143	0.683	27
11-Months Ahead	0.060	0.189	0.142	0.669	26
12-Months Ahead	0.064	0.208	0.129	0.662	25

Theil inequality statistics are also computed for both of the benchmark alternatives to which the transfer function simulations are compared. Those for the univariate ARIMA equation are summarized in Table 6, while those for the random walk procedure are shown in Table 7. Data in those tables exhibit good simulation characteristics. U-coefficients for both methodologies are close to zero and their respective covariance proportions exceed 0.72 for all step-lengths examined.

Table 6: Univariate ARIMA Model Simulation Results

	Theil-U	U^m	U^s	U^c	Observations
1-Month Ahead	0.017	0.022	0.001	0.978	36
2-Months Ahead	0.025	0.047	0.002	0.951	35
3- Months Ahead	0.031	0.056	0.002	0.942	34
4-Months Ahead	0.037	0.082	0.008	0.910	33
5-Months Ahead	0.042	0.128	0.016	0.856	32
6-Months Ahead	0.048	0.162	0.027	0.811	31
7-Months Ahead	0.054	0.183	0.033	0.784	30
8-Months Ahead	0.061	0.189	0.029	0.782	29
9-Months Ahead	0.067	0.198	0.027	0.775	28
10-Months Ahead	0.073	0.215	0.024	0.761	27
11-Months Ahead	0.077	0.236	0.023	0.742	26
12-Months Ahead	0.081	0.255	0.021	0.724	25

Table 7: Random Walk Simulation Results

	Theil-U	U^m	U^s	U^c	Observations
1-Month Ahead	0.016	0.003	0.006	0.990	36
2-Months Ahead	0.024	0.007	0.013	0.981	35
3- Months Ahead	0.030	0.006	0.012	0.983	34
4-Months Ahead	0.036	0.011	0.021	0.968	33
5-Months Ahead	0.040	0.019	0.034	0.947	32
6-Months Ahead	0.045	0.031	0.048	0.921	31
7-Months Ahead	0.051	0.038	0.054	0.908	30
8-Months Ahead	0.056	0.041	0.051	0.908	29
9-Months Ahead	0.061	0.043	0.050	0.907	28
10-Months Ahead	0.065	0.049	0.050	0.900	27
11-Months Ahead	0.068	0.059	0.051	0.890	26
12-Months Ahead	0.071	0.068	0.048	0.885	25

In-bond manufacturing employment forecast RMSEs for both LTF models are further compared to the RMSEs from the other approaches in order to obtain relative measures of accuracy across all 12 step-lengths. Modified Theil inequality coefficients for both sets of LTF simulations are shown in Tables 8 and 9. Relative to each other, there is no appreciable accuracy gain or loss associated with either LTF specification strategy. Both categories of LTF simulations compare favorably, however, to each of the benchmark procedures. Modified Theil inequality coefficients for the LTF equations consistently exhibit values lower than 1.0 for all 12 step lengths when compared to the benchmarks. On average, the LTF model RMSEs are more than 18 percent smaller than those associated with the univariate model and more than 12 percent smaller than those associated with random walk methodology.

Table 8: Aggregate U.S. Industrial Production Index LTF RMSE Comparisons

	RMSE	MU1	MU2	MU3	Observations
1-Month Ahead	1,352	1.025	0.837	0.886	36
2-Months Ahead	2,028	1.027	0.860	0.901	35
3- Months Ahead	2,540	1.002	0.852	0.884	34
4-Months Ahead	3,002	0.985	0.852	0.881	33
5-Months Ahead	3,268	0.963	0.815	0.850	32
6-Months Ahead	3,627	0.961	0.788	0.839	31
7-Months Ahead	4,141	0.974	0.784	0.848	30
8-Months Ahead	4,639	0.988	0.783	0.858	29
9-Months Ahead	5,140	1.001	0.784	0.873	28
10-Months Ahead	5,529	1.009	0.775	0.879	27
11-Months Ahead	5,908	1.014	0.776	0.897	26
12-Months Ahead	6,296	1.018	0.786	0.920	25
Average		0.997	0.808	0.876	

$MU1=RMSE_{LTF1}/RMSE_{LTF2}$
$MU2=RMSE_{LTF1}/RMSE_{ARIMA}$
$MU3=RMSE_{LTF1}/RMSE_{RW}$

Table 9: Disaggregated U.S. Industrial Production Index LTF RMSE Comparisons

	RMSE	MT1	MT2	MT3	Observations
1-Month Ahead	1,319	0.976	0.816	0.864	36
2-Months Ahead	1,975	0.974	0.837	0.877	35
3- Months Ahead	2,535	0.998	0.850	0.882	34
4-Months Ahead	3,048	1.015	0.865	0.894	33
5-Months Ahead	3,393	1.038	0.846	0.883	32
6-Months Ahead	3,773	1.040	0.819	0.873	31
7-Months Ahead	4,251	1.027	0.805	0.870	30
8-Months Ahead	4,696	1.012	0.793	0.868	29
9-Months Ahead	5,137	0.999	0.784	0.873	28
10-Months Ahead	5,480	0.991	0.768	0.872	27
11-Months Ahead	5,828	0.986	0.766	0.885	26
12-Months Ahead	6,182	0.982	0.771	0.903	25
Average		1.003	0.810	0.879	

$MT1=RMSE_{LTF2}/RMSE_{LTF1}$
$MT2=RMSE_{LTF2}/RMSE_{ARIMA}$
$MT3=RMSE_{LTF2}/RMSE_{RW}$

Because the estimation results and simulation outcomes for both versions of the LTF equations are fairly similar, it is not possible to reach a definitive conclusion with respect to which approach should be employed. The disaggregated index specification is somewhat attractive because it permits examining the impact of variegated business cycle phases. Under such a scenario, an LTF specified in this manner would be able to examine the impacts of differential economic conditions in the export market on the local economy. If one sector lags behind others during a target market business cycle expansion, that scenario can be simulated with an LTF equation that utilizes industrial production sub-indexes. In some regional economies, however, it may not be possible to identify the various sectors of relevance in the export market. In those cases, employment of an aggregate industrial production index may offer a satisfactory alternative.

No matter which approach is selected, the business cycle linkages between industrial conditions in the United States and metropolitan Chihuahua are fairly prominent. Given this, slack labor market conditions in this metropolitan economy are likely to persist as long as United States growth rates remain lethargic. Because in-bond manufacturing plays an important role in municipal public finance, local government authorities will find it difficult to engage large-scale infrastructure investment efforts under current funding mechanisms. Rather than allow important projects to be periodically derailed by the cyclical nature of this industry, it is may now be advisable for municipal authorities in Chihuahua City and other areas of Mexico to seek bonding authority as a means of smoothing out cyclical revenue and expenditure requirement mismatches.

All of the econometric results obtained point to an industry that reacts very quickly to external market stimuli. Such industries typically require flexible regulatory environments in order to thrive. At present, the public administrative setting in Mexico does not govern its domestic markets in such a manner and is suspected of causing the maquiladora sector to operate at less than full capacity in recent years (Fullerton and Barraza, 2003). A more streamlined regulatory environment would probably help in-bond assembly markets in non-border regions such as the city of Chihuahua to recover more quickly from cyclical cutbacks as well as continue to attract direct foreign investment flows.

CONCLUSION

The Mexican in-bond assembly, or maquiladora, industry has expanded into interior regions of the country and represents an important source of direct foreign investment and employment. The migration of the maquiladora industry into the interior of Mexico has caused several regional economies to become more closely linked to the business cycle of the United States. Measurement of these linkages represents an important step toward eventually understanding the impacts of globalization on developing economy regional labor markets.

A natural progression is replication and extension of an earlier study completed for one of the border economies in Mexico. This paper does so by measuring short-run maquiladora payroll dynamics for the more interior geographic region of Chihuahua City. While a non-border urban economy, the maquiladora industry has been present there for more than twenty years. Consequently, data constraints are less binding for that metropolitan area relative to other non-border regions where the maquiladora industry has only recently migrated.

Two different linear transfer function models are estimated, one with an aggregate United States industrial production index and the other with disaggregated industrial production index components that reflect foreign investment flows to the city of Chihuahua. Estimation results in both cases indicate that the in-bond assembly industry reacts quickly to changes in economic conditions that affect costs of production and/or export prospects. Simulation exercises with both equations generate outcomes that compare favorably to univariate ARIMA and random walk benchmark alternatives.

Given the results obtained, replication of this modeling effort for other developing country regional labor markets may be feasible. Doing so would potentially enable researchers to better understand payroll dynamics in an era of increased cross-border economic linkages between industrial and developing economies. That ultimately can help in the design of more effective economic and business policies in those regions. While this paper has been conducted with respect to a metropolitan economy in Mexico, other markets that can also be studied include many in Latin America, Southern Asia, and Eastern Asia. All of these regions are characterized by fairly sizable inflows of direct foreign investment.

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