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Employment Linkages in Technology Manufacturing in Texas

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Abstract: This study examines the relationship among employment in three technology manufacturing industries in Texas. The study focuses on employment in the following manufacturing industries: computer and peripheral equipment, communication equipment, and semiconductor and other electronic components. We utilize time series econometric techniques in order to ascertain the extent to which employment is related among these technology sectors. Based on results from cointegration tests, we conclude that these employment series do not share a common stochastic trend. However, results from the vector autoregession model and the corresponding impulse response functions indicate the presence of significant linkages among employment in these industries. The findings are consistent with the economic environment of the technology industry being characterized by highly efficient operations in a competitive, integrated marketplace.

Key words: Technology industries, employment, vector autoregression

INTRODUCTION

Changes in supply chains have altered the economic landscape. In particular, phenomenal growth has occurred in information technology and e-commerce over the last decade and the lines between related industries have blurred as a result. In this environment, knowledge management and highly skilled workers are critical elements for developing and sustaining competitive advantage. Consequently, firms have responded by focusing on operational strategies that emphasize competitiveness, productivity and the ability to change. Many firms regularly alter their labor resources in real time as part of their demand management practices. Moreover, with the short product life cycles and the high speed in which innovation takes place in the technology industry (broadly defined), we should see sectors that share substitutable resources exhibiting strong responses to changes initiating in closely related industries. The main purpose of this paper is to examine the extent to which unexpected changes in one technology sector are transmitted to other closely related sectors. More generally, our focus is on identifying and documenting the employment linkages that exist within the technology manufacturing industries in the state of Texas. Knowledge of how employment in one industry responds to unexpected changes in related industries will assist firms in formulating and implementing their plans for resource utilization.

We study the linkages in employment among the following manufacturing sectors: communication equipment, computer and peripheral equipment and semiconductor and other electronic components. Demand for goods and services plays a critical role in the labor requirements of firms. As such, changes in the relative demands across these sectors will be marked by changes in employment. Given that the human capital and skill sets are fairly transferable among workers in these technology sectors, we expect some degree of cross-dynamics. Thus, it is likely that an unexpected change in business activity (e.g., an increase in employment) in one sector will be transmitted to other related sectors. In fact, our results indicate that the magnitude of these linkages is nontrivial and that in some cases the effects of unexpected changes in one sector on another sector persist for several months.

While a number of studies have examined employment and or wage relationships associated with employment in a variety of industries, very little academic research has concerned itself with employment in the technology industry, especially on a regional level. For example, Carlino and Defina (2004) studied the co-movement in employment across sectors and states over the business cycle. They found there to be much greater cohesion across states for a given sector than across different sectors within a state. Ewing *et al*. (2005) examined the transmission of employment shocks in three geographically dispersed but economically linked

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metropolitan statistical areas. Generally speaking, their results highlight how unexpected changes in employment in one area ultimately affect employment in other areas. Others have looked at compensation in various industries, how wage growth and unemployment may be related and how integrated manufacturing (e.g., JIT, TQM and lean production) impacts compensation schemes (Aaronson and Sullivan, 2001; Snell and Dean, 1994).

In a multi-country study, Caporale and Haq (2002) focused on the manufacturing sector and differences in employment and wages between skilled and unskilled workers. They concluded that changes in employment come from external shocks, especially in the high technology industries and not from industry-specific shocks. Changing industry employment and industry employment shifts may be behind much of the wage inequality that exists between service and goods producing industries according to Valletta (1997). Finally, Browne (1994) distinguishes the features between goods producing and services producing sectors with respect to inventory and demand-supply management. Present study differs from those outlined above in that we focus on one particular region (Texas) and examine shocks within one manufacturing industry, namely the high technology sector. Thus, our work further develops the finding by Ewing *et al.* (2005) on the existence of significant transmission of shocks among supply-chain related sectors and builds on the findings of manufacturing employment/wage studies by Browne (1994), Snell and Dean (1994), Valletta (1997), Aaronson and Sullivan (2001), Caporale and Haq (2002) and Carlino and Defina (2004). Our approach utilizes a time series estimation technique that involves the estimation of a vector autoregression and the computation of generalized impulse response functions. The methodology allows us to explicitly examine how shocks in one sector are transmitted to other sectors.

MATERIALS AND METHODS

Employment data are from the US Bureau of Labor Statistics, Employment and Earnings (http://www.bls.gov). The study uses employment data from three separate technology industries in Texas; namely, (1) computer and peripheral equipment (2) communications equipment manufacturing and (3) semiconductor and other electronic components manufacturing. For each of these sectors the monthly data are seasonally adjusted and cover the period from January 1990 to May 2005. In the analyses that follow, we use the natural log of each employment series. Table 1 presents descriptive statistics, while Fig. 1 and 2 show

Table 1: Descriptive statistics for monthly employment

	COMM	PERI	SEMI	DCOMM	DPERI	DSEMI
Mean	3.19	3.29	3.98	-0.0029	-0.0010	0.0015
Maximum	3.54	3.53	4.37	0.1473	0.0376	0.0478
Minimum	2.83	3.03	3.65	-0.0854	-0.0606	-0.0460
Std. Dev.	0.2171	0.1365	0.2210	0.0205	0.0131	0.0131

Notes: COMM, PERI and SEMI are the natural log of employment for computer and peripheral equipment, communications equipment manufacturing and semiconductor and other electronic components manufacturing, respectively. The first difference operator is denoted D

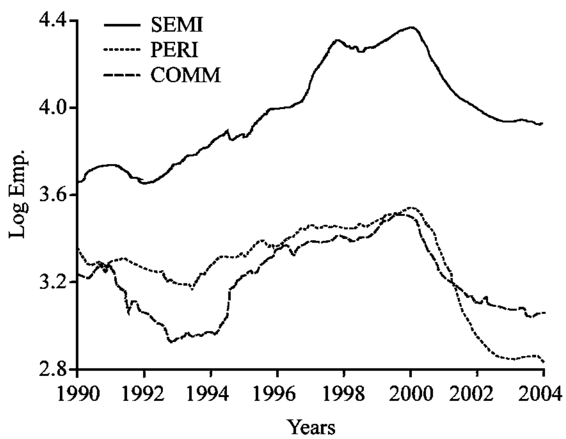

Fig. 1: Employment Levels Over Sample Period January 1990 to May 2005

Note: COMM, PERI and SEMI are the natural log of employment for computer and peripheral equipment, communications equipment manufacturing and semiconductor and other electronic components manufacturing, respectively

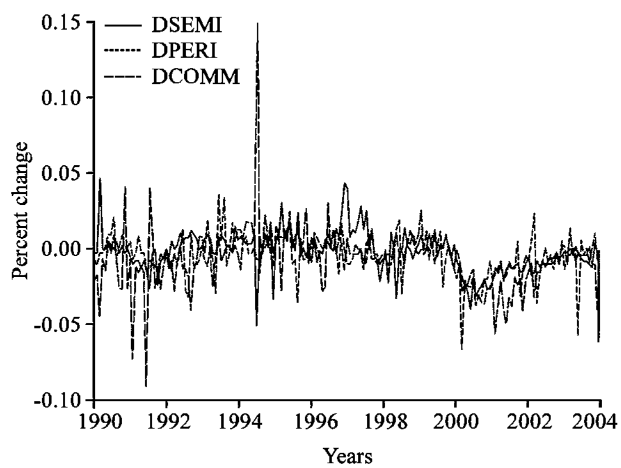

Fig. 2: Changes in Employment Over Sample Period January 1990 to May 2005

Note: DCOMM, DPERI and DSEMI are first-differences of the natural log of employment for computer and peripheral equipment, communications equipment manufacturing and semiconductor and other electronic components manufacturing, respectively plots of the levels and first-differences of the employment series, respectively. It is interesting to note that while employment follows similar patterns across the three technology sectors, the movements over time are not perfectly correlated.

The importance of first pre-testing the data series for stationarity cannot be overstated. This is because shocks (i.e., unanticipated changes) to a stationary series are only transitory in nature, that is, the effects die out over time. In the case of employment this means that a sudden, unexpected increase in the level of workers employed in a sector (in isolation of the other sectors) will cause the series to increase; however, over time the level of employment will eventually return to some normal, baseline value. In contrast, if the employment series is nonstationary, then a sudden, unexpected increase will lead to a permanent increase in the level of employment and the variance will increase without bound. Findings of nonstationary employment are common in the economics literature (Ewing *et al.* 2005). In fact, this result is consistent with long run growth patterns found for most economies in terms of both population and real output (i.e., changes in the level of employment are permanent in nature while changes in employment growth rates are transitory). Estimation of the vector autoregression (VAR) model requires the data series be stationary and if each series is not stationary, a data transformation such as first-differencing the data may be required (Enders, 2004).

In order to determine whether or not each of the employment measures is stationary, we perform unit root tests based on the method of Dickey and Fuller (1981).

Results of the augmented Dickey-Fuller test (ADF) are shown in Table 2 and indicate that each employment series is integrated of order one (I(1)) and thus the first difference of employment is stationary.

Two or more I(1) time series are said to be cointegrated if some linear combination of them is stationary. Tests for cointegration indicate whether or not a stable log-run relationship exists among a set of variables, that is, they share a common stochastic trend. Given the multivariate nature of this study, we use the system of equations approach proposed by Johansen (1991) and Johansen and Juselius (1990) to test for the presence of cointegration. In terms of our purposes, a finding of cointegration means that we would estimate a VAR augmented with error correction term(s) in order to avoid omitted variable bias. However, if no evidence of cointegration is detected then it is appropriate to estimate a standard vector autoregression model. Results shown in Table 3 reveal no evidence of cointegration. Thus, we proceed to the estimation of the VAR model.

Table 2: Augmented Dickey-Fuller unit root test results

	Level	First-difference
COMM	-1.4845	-2.7059**
PERI	-1.3533	-4.9842*
SEMI	-1.5595	-4.5993*

Notes: COMM, PERI and SEMI are the natural log of employment for computer and peripheral equipment, communications equipment manufacturing and semiconductor and other electronic components manufacturing, respectively. * (**) denotes significance at 1% (10%) level or less based on critical values found in Mackiunon (1991)

Table 3: Cointegration test results

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical value	Prob.**
(a) Uurestricted Cointegration Rank Test (Trace)				
None	0.092121	21.48300	29.79707	0.3282
At most 1	0.020606	4.086955	15.49471	0.8964
At most 2	0.001882	0.339122	3.841466	0.5603

(b) Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen. Statistic	5% Critical value	Prob.**
None	0.092121	17.39605	21.13162	0.1541
At most 1	0.020606	3.747833	14.26460	0.8850
At most 2	0.001882	0.339122	3.841466	0.5603

Max-eigenvalue test indicates no cointegration at the 0.05 level, Trace test indicates no cointegration at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKiunon-Haug-Michelis (1999) p-values, Notes: CE denotes cointegrating equation. Prob is the actual probability value. The tests allow for a linear deterministic trend in the data. 4 lags were included

Recall that we are interested in the response of changes in employment in one sector to shocks in the other employment sectors. Vector autoregressive (VAR) models, Granger causality/block exogeneity tests and impulse response functions are ideal for this type of dynamic analysis. In terms of the latter technique, the conventional impulse response method is often criticized because results are subject to the assumption of orthogonality. That is, they may differ markedly depending on the ordering of the variables in the VAR (Lutkenpohl, 1991). The *generalized* methodology of Pesaran and Shin (1998) overcomes this problem. The generalized impulse responses are not sensitive to the ordering of the variables.

The three-equation VAR(m) model is given by the following, where m represents the number of lags or (vector) autoregressive terms:

$$\begin{aligned}
DCOMM_t &= a_{10} + \sum_{i=1}^{m} a_{i1} DCOMM_{t-i} + \sum_{i=1}^{m} b_{i1} DPERI_{t-i} \\
&\quad + \sum_{i=1}^{m} c_{i1} DSEMI_{t-i} + v_{1t} \\
DPERI_t &= a_{20} + \sum_{i=1}^{m} a_{i2} DCOMM_{t-i} + \sum_{i=1}^{m} b_{i2} DPERI_{t-i} \\
&\quad + \sum_{i=1}^{m} c_{i2} DSEMI_{t-i} + v_{2t} \\
DSEMI_t &= a_{30} + \sum_{i=1}^{m} a_{i3} DCOMM_{t-i} + \sum_{i=1}^{m} b_{i3} DPERI_{t-i} \\
&\quad + \sum_{i=1}^{m} c_{i3} DSEMI_{t-i} + v_{3t} \qquad (1)
\end{aligned}$$

In matrix notation, the VAR(m) model is written compactly as:

$$g_t = a_0 + \beta(L)g_t + v_t \quad (2)$$

Here, we let g_t be the 3x1 vector of employment growth rates (DCOMM, DPERI and DSEMI, respectively), a_0 the constant term vector and v_t be the corresponding disturbance vector (i.e., v_{1t}, v_{2t} and v_{3t} are the shocks to the three employment growth rates). L denotes a polynomial in the lag operator, thus, the right-hand-side of Eq. 2 contains only past values of the three growth rates as well as the constant and error terms.

Now consider the following moving average representation of the three-equation VAR(m) model, where the constant terms may be ignored:

$$g_t = \Psi(L)v_t \quad (3)$$

Let $E(v_t v'_t) = \Sigma_v$ such that shocks are contemporaneously correlated. The generalized impulse response function of g_i to a unit (one standard deviation) shock in g_j is given by:

$$\Psi_{ij,h} = (\sigma_{ii})^{-1/2}\,(e'_j \Sigma_v e_i) \quad (4)$$

where, σ_{ii} is the ith diagonal element of Σ_v, e_i is a selection vector with the ith element equal to one and all other elements equal to zero and h is the horizon (in our case, measured in monthly increments).

RESULTS

Key features of the generalized impulse response function are that the responses are invariant to any re-ordering of the variables in the VAR and as orthogonality is not imposed, it allows for meaningful interpretation of the initial impact response of each variable to shocks to any other variable. Generally speaking, the generalized impulse response function provides more robust results than the orthogonalized method. In the study of economic systems in which events may occur that simultaneously or contemporaneously affect each sector, the ability to capture these immediate responses of endogenous variables to shocks is especially appealing.

Prior to discussing the impulse responses, we first make note of several interesting findings from the estimation of the VAR, the results of which are presented in Table 4. The order of the VAR was determined to be one based upon LR, AIC and SBC criteria. In contrast to the DCOMM and DSEMI equations, the pure autoregressive term in the DPERI equation is not statistically significant. This finding implies that changes in the peripheral sector depend more on past changes in the other two sectors than on its own past changes. This lack of momentum is also consistent with peripheral firms being more apt to change their workforce relatively more quickly than the other sectors. Turning to Table 5, the results of the Ganger-causality/block exogeneity test results indicate that related sectors are indeed good predictors, jointly and independently, of changes in employment in any of the technology sectors examined. This high degree of employment interdependence is indicative of industries that share and/or compete for workers with highly transferable skills. That is, in terms of employment, these related technology sectors hire and often train, workers that are able to take their human capital to other firms either in the same sector or in the other sectors. Labor economic theory would suggest, therefore, that these workers should be more inclined to pay for their on-the-job and related training since it carries with them to other (potential) employers.

Table 4: VAR results

	DCOMM	DPERI	DSEMI
$DCOMM_{t-1}$	0.1759[a]	0.1081[b]	0.1434[a]
	[2.4851]	[2.3250]	[3.5389]
$DPERI_{t-1}$	0.1923[c]	0.0897	0.1475[b]
	[1.6645]	[1.18307]	[2.2318]
$DSEMI_{t-1}$	0.4323[a]	0.2165[a]	0.4273[a]
	[3.8376]	[2.9273]	[6.6283]
Constant	-0.0028[c]	-0.0009	0.0014[c]
	[-1.9412]	[-0.9436]	[1.6724]
R-squared	0.1613	0.1093	0.3257
Adj. R-squared	0.1473	0.0943	0.3143
S.E. equation	0.018983	0.012467	0.010863
F-statistic	11.4761	7.3199	28.8135

Notes: Superscripts [a], [b], [c] denote significance at 1, 5 and 10% levels, respectively and t-statistics reported in square brackets. COMM, PERI and SEMI are the natural log of employment for computer and peripheral equipment, communications equipment manufacturing and semiconductor and other electronic components manufacturing, respectively. The first difference operator is denoted D

Table 5: VAR Granger Causality/Block Exogeneity Wald Tests

Excluded	Chi-sq	df	Prob.
Dependent variable: DCOMM			
DPERI	2.770477	1	0.0960
DSEMI	14.72702	1	0.0001
All	23.21413	2	0.0000
Dependent variable: DPERI			
DCOMM	5.405426	1	0.0201
DSEMI	8.569317	1	0.0034
All	14.30684	2	0.0008
Dependent variable: DSEMI			
DCOMM	12.52391	1	0.0004
DPERI	4.980944	1	0.0256
All	21.93995	2	0.0000

Notes: COMM, PERI and SEMI are the natural log of employment for computer and peripheral equipment, communications equipment manufacturing and semiconductor and other electronic components manufacturing, respectively. The first difference operator is denoted D. Degrees of freedom is denoted by df

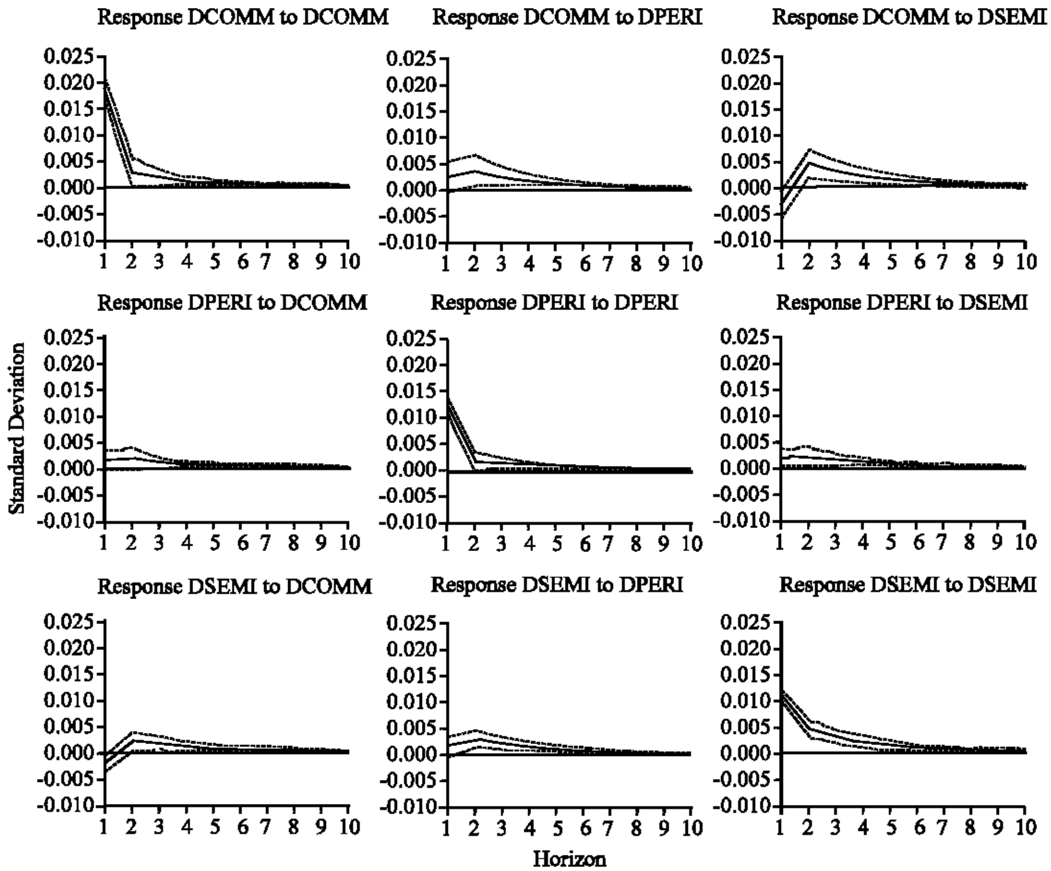

Fig. 3: Generalized impulse response functions

Note: Horizontal axis is measured in monthly horizon and vertical axis is standard deviation. DCOMM, DPERI and DSEMI are first-differences of the natural log of employment for computer and peripheral equipment, communications equipment manufacturing and semiconductor and other electronic components manufacturing, respectively. Dashed lines represent +/- two standard errors and may be used to determine statistical significance

The final step in our analysis is the computation of the Generalized Impulse Response Functions (GIRF). Figure 3 presents the GIRFs corresponding to each of the employment equations. "Own" shocks (represented along the diagonal) are most persistent in the semiconductor industry while own shocks in the communication and peripheral sectors die out much quicker. By itself, this finding suggests that the semiconductor sector is the least resilient of the three as it takes much longer for this sector to return to normal following a disturbance.

The GIRF results also reveal a number of cross-effects in technology employment indicating that shocks transmit from one sector to another. In general, the effects of employment shocks in the semiconductor sector persist the longest, both in terms of own shocks and in terms of the transmission of shocks. Employment shocks in the peripheral sector are more uniformly experienced across the sectors. Shocks to the communication sector transmit the least across sectors and when they do, are of a slightly lower magnitude.

DISCUSSION

This study provides empirical evidence as to the extent to which unexpected changes in one technology manufacturing sector are transmitted to other closely related sectors and therefore may be used by firms for strategic planning purposes. The results support the generalization that the economic environment of the technology industry is characterized by highly efficient operations in a competitive, integrated marketplace. Technology manufacturing firms alter their work force quickly in response to demand and production changes and workers are quickly able to move from one sector to another. The industry exhibits a high degree of labor resource substitutability and the sectors are closely related. The findings support the earlier work on labor market linkages (Carlino and Defina, 2004; Ewing *et al*., 2005) and has added to the literature by quantifying the employment linkages in the technology industry. Future work may focus on examining the extent to which the technology industry is linked to macroeconomic factors such as GDP and monetary policy and thus provide insight as to the source of the shocks.

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