RELATIONSHIPS BETWEEN PROPOSED MEASURES OF TECHNOLOGICAL CHANGE AND EMPLOYMENT IN THE MANUFACTURING SECTOR

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ABSTRACT

Technological change has an impact on the economy of a country in terms of productivity and negative effects on employment in manufacturing. Different technology measures have been used to study the relationship between technology and employment. It is not clear from the literature how these measures relate to employment in manufacturing. In this study, we investigate the relationship between technology measures proposed in the literature (labor productivity, total factor productivity (TFP), GDP per capita, GDP per hour worked, and research and development (R&D) in manufacturing) and employment in the manufacturing sector in the United States. Using transfer function time series analysis, results showed that labor productivity, total factor productivity, and GDP per capita were positively related to employment in manufacturing. GDP per hour worked was not related to employment in manufacturing. Only R&D in manufacturing had a negative impact on employment in manufacturing. If improvement in technology is having a negative effect on employment, then from these results, it seems that the only true measure of technological change is R&D in manufacturing.

INTRODUCTION

The U.S. labor market has witnessed a sharp decrease in employment in manufacturing since the year 2000 (Figure 1). It is generally acknowledged that trade and technology are the two forces that predominantly effect employment in the United States and other developed countries. New technologies in the workplace lead to automation of tasks previously performed by low skilled workers, which contributes to a decrease in employment of unskilled workers and to more demand for skilled labor (Autor and Dorn, 2013; Edwards and Lawrence, 2013).
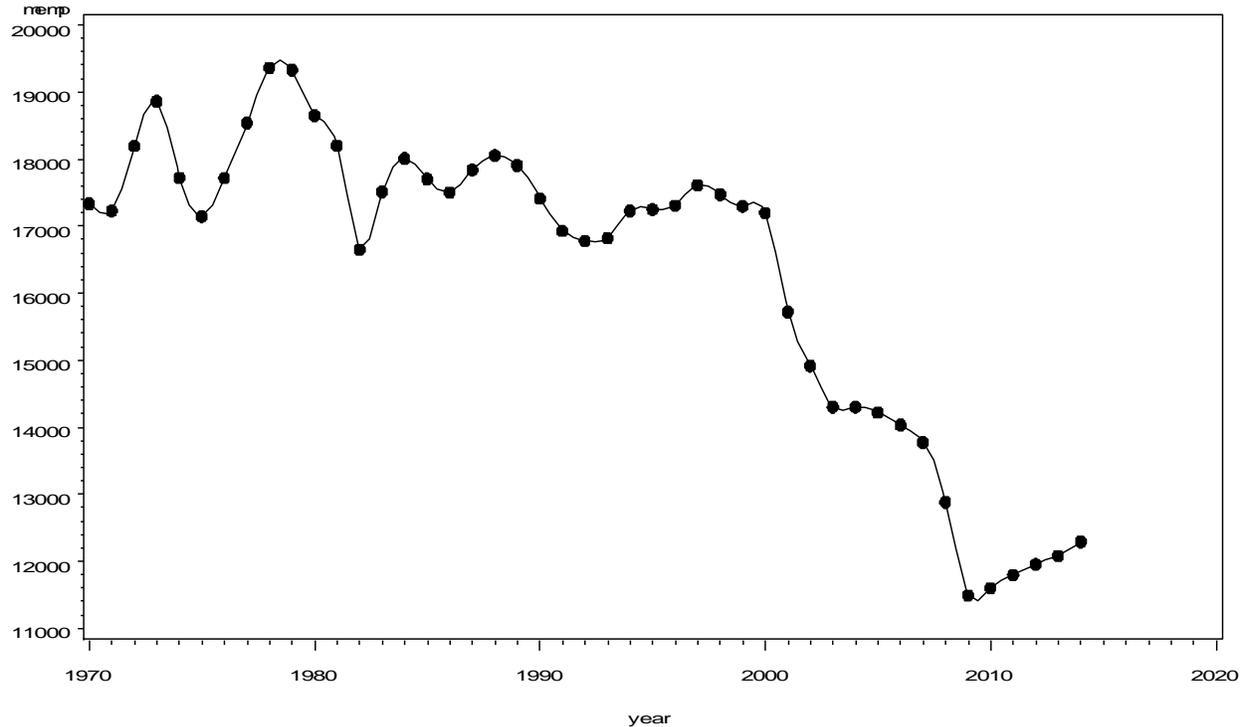
FIGURE 1. PLOT OF EMPLOYMENT IN MANUFACTURING (MEMP) OVER YEARS

There have been several indexes used to measure technological change. Labor productivity and total factor productivity (TFP) are two indexes commonly used to represent technological change. Both are based on comparing input to output. Graham (2016)) pointed out that both indexes have shortfalls in this regard. Technology change is not the only factor that changes labor and total factor productivity. For example, Changes in the quantity of input because of changes in input prices change labor and total factor productivity.

Another measure of technology proposed by Santacreu (2016) of the Federal Reserve Bank of St. Louis is GDP per hour worked. He argued that it might be a better measure of labor productivity than GDP per capita, which has been commonly used. GDP per capita can be influenced by outside variables such as fertility and mortality rates, number of hours worked, and the composition of the labor force.

Kim (2012) reported on indicators used for measuring technological change. R&D is a globally accepted indicator used by the Organization for Economic Cooperation and Development (OECD) for economic growth in terms of technological change.

The literature is mixed on the effect of technology on employment in manufacturing. It is important to determine the relationship of technological change on employment in manufacturing. In this study, we investigate, using time series analysis, the relationship between different technology indexes and employment in manufacturing. Indexes used are labor productivity, TFP, GDP per

hour worked, GDP per capita, and R&D in manufacturing. As far as we know, this study is the first to utilize a state-of-the-art time series analysis of this employment problem. It should shed new light on the effect of technological change on employment in manufacturing and will determine which index, if any, is a true measure of technological change in the sense of having a negative effect on employment.

LITERATURE REVIEW

Kuehn and Braschler (1986) reported on employment losses (for the period 1975-1980) due to changes in technology measured by the labor-output ratio, which was defined as the number of employees per dollar of shipments. Increase in labor efficiency induced primarily by new technology, decreased employment in a number of industries. Decline in employment because of technology was 18.5% in the chemical industry. The decline was 21.2% in the electric and electronic industry. In addition, labor saving technology in the textile industry contributed to 18.5% loss in employment. Also, employment in the furniture and fixture industry declined by 20.1%. The authors estimated that 1.8 million jobs were lost from changes in the labor-output ratio.

Autor et al. (2015) reported that exposure to technological change had a negative effect on employment in clerical occupations and routine task-intensive production in the manufacturing as well as the non-manufacturing sectors. However, it was found that exposure to technological change had no effect on overall employment.

Chang and Hong (2013), in a study on change in technology (measured by total factor productivity) and job creation for the 1958 to 1996 period, reported that the effect of technology on labor employment varied across the manufacturing industry. However, the majority of the manufacturing industries hire workers when there is improvement in technology. Contrary to common belief, technological innovation was found to create more jobs in the short and long run.

Freeman et al. (1995) discussed the employment effects of information and communication technology (ICT) in different parts of the world. ICT has had positive and negative effects on employment as is well illustrated in the automobile industry and computers in financial services. In East Asia, ICT has contributed to high output growth, and high growth in productivity and full employment. However, in Europe and Latin America, ICT has contributed more to job reduction than to job creation; this shift to a knowledge-based economy through ICT has had adverse effects on employment and wages of unskilled manual workers.

Jenkins (2008) investigated the effects of trade and technological change on employment in South Africa. His analysis included regressing the log of employment, as the dependent variable, on the independent variables, namely the cost of labor relative to capital and trade variables, such as share of imports in domestic demands, share of exports in total output, and time trend for technological change. He found that both technology and trade had a negative effect on growth in employment in manufacturing in the 1990s. Trade and technology, however, were not the only factors contributing to reduced employment (R^2 in the regression was less than 0.28). Other important factors, not in the regression that were thought to have impacts on employment, were

macroeconomic conditions, economic institutions, and social norms. The author argued that these factors, from a policy point of view, should have higher priority than technology and trade in a job creation strategy.

Fisher (2004), in a commentary on why we are losing jobs in manufacturing, stated that the main reason is labor-saving progress in technology. He stated, "An economy undergoing rapid technological progress is one in which some sectors are booming and others are senescent." Manufacturing is senescent and is no longer a primary source of economic growth. The percentage of people employed in manufacturing has declined steadily since the 1960s. The rising income in a prosperous economy like the United States has created more demand for services that resulted in a smaller share of the workforce employed in manufacturing.

Rico (1996), using data from nine firms, analyzed the effect of technological progress in terms of automation on employment in manufacturing. The author concluded that automation has not substantially affected employment in manufacturing. While some jobs were eliminated, others were created and filled by the displaced employees within the same firms. However, it was pointed out that in the long run the prospects for employment in manufacturing were not optimistic.

Chang and Hong (2006), in a study involving 458 manufacturing industries for the period 1958-1996, found that the effect of technology, measured by total factor productivity (TFP), on employment varied greatly across industry. Far more industries showed an increase in employment in the short run because of a positive change in technology, yet these results were contradictory to results by Kiley (1998), who found a negative correlation between labor productivity and employment. Chang and Hong (2006) argued that their results did not conflict with those of Kiley since different measures for technology were used in these studies. Kiley used labor productivity as the measure while Chang and Hong used TFP. Chang and Hong argued that TFP was a better measure of technological change since labor productivity reflects input mix and not only improved efficiency. They argued that TFP, rather than labor productivity, was a natural measure of technology.

In their study, Brynjolfsson and McAfee (2011) argued that IT and automation are contributing factors to reduced employment in manufacturing. Acemoglu et al. (2014), using data from U.S. manufacturing over the period 1980 to 2009, in their study concluded that IT-intensive industry did not show an increase in productivity, which could imply that IT had no effect on reducing employment in manufacturing.

Mullen et al. (2009) studied the effect of investment in technology (measured by spending on research and development and on investment in information and communication technology) by manufacturing companies on employment. They concluded that technology investment significantly decreased employment of unskilled workers in manufacturing.

METHODS

Time Series Transfer Function Model

The transfer function methodology is the best approach to modeling a linear relationship between an input and output time series. A time series transfer function model relating a stationary output series y_t to a stationary input series x_i can be expressed in general as:

$y_t = v(B) \, x_t + a_t$ (1)

where $v(B) = w(B)B^c/\eta(B)$.   (1a)

Here, $w(B) = w_0 - w_1 B - \ldots - w_s B^s$

$\eta(B) = 1 - \eta_1 B - \ldots - \eta_r B^r$.

and c represents the time delay (or lag) until the input variable x_t produces an effect on the output variable y_t.

We assume that the input series follows an ARMA process, $\frac{\varphi(B)}{\theta(B)} x_t$. The function v(B), with its lags, is determined from the cross correlations between the white noise input series $\frac{\varphi(B)}{\theta(B)} x_t$ and the output series $\frac{\varphi(B)}{\theta(B)} y_t$; namely the significance at a given lag and the pattern of the cross correlations over lags (Wei, 2006).

For instance, if the cross correlation is significant at only lag 0, then Equation (1) becomes $y_t = w_0 x_t + a_t$.

Once v(B) is identified, one can express a_t in Equation(1) as $a_t = y_t - v(B) \, x_t$ (2) and identify the appropriate time series model for Equation (2). With a_t known, one can determine the final model in Equation (1). For example, if a_t were identified using its autocorrelation and partial autocorrelation characteristics as an AR(1) process ($a_t (1-\phi B) = e_t$), then a_t in Equation (1) would be replaced by $e_t/(1-\phi B)$, where e_t is random error.

If y and x are not stationary, then the series can be differenced to make them stationary. Stationarity was determined by the autocorrelation rate of decay over lags and by the augmented Dickey-Fuller test (Wei, 2006; Cryer and Chan, 2008). The SAS software was used to specify v(B), to estimate the parameters of the model, and to test for their significance.

DATA

Data for this study came from the Federal Reserve St. Louis economic data (FRED) and the Bureau of Labor Statistics (BLS). The Labor productivity index, as output per hour all persons and total factor productivity (measured as percent change from previous year) for the manufacturing sector for the period 1988 – 2014, were obtained from the BLS, U.S. Department of Commerce. Data for GDP per capita in dollars for the period 1970-2014 were obtained from FRED. Yearly data for

GDP per hour worked in the U.S. (1970-2014), R&D in manufacturing (1988- 2014) (measured as percent change from previous year), total factor productivity index (national level), and employment in manufacturing in 1000 (1970-2014) were obtained from the FRED database..

EMPIRICAL RESULTS

R&D in Manufacturing

The identified time series model (from equation (1)) relating R&D data in manufacturing (Figure 2) as the input series to employment in manufacturing (differenced once for stationarity) as the output series is:

$$y(1)_t = 247.69 \ -1701.9 \ x_t + e_t \ , \tag{3}$$

where $y(1)_t = y_t - y_{t-1}$

      y = employment in manufacturing on a yearly basis.

x = Percent change in R&D in manufacturing from the previous year and e_t = random error

All the coefficients in Equation (3) were highly significant ($p < 0.001$). As can be seen from (3), there is a negative relationship between change in employment in manufacturing and the percent of change in R&D in manufacturing. Also, the cross correlation between the two series was negative and highly significant ($r_k = -0.828$ at lag 0). This means that as investment in research and development in manufacturing increases employment in manufacturing decreases. This implies that an improvement in technology has the effect of replacing jobs in manufacturing. If technology has the effect of replacing workers, the R&D in manufacturing proved to be a true measure of technology change.

When R&D in manufacturing, measured as an index, was used, the results were the same, namely a negative highly significant cross-correlation of -0.82 at lag zero between employment in manufacturing and R&D. Unlike R&D in the manufacturing sector, R&D for all industry did not show a significant relationship with employment in manufacturing.
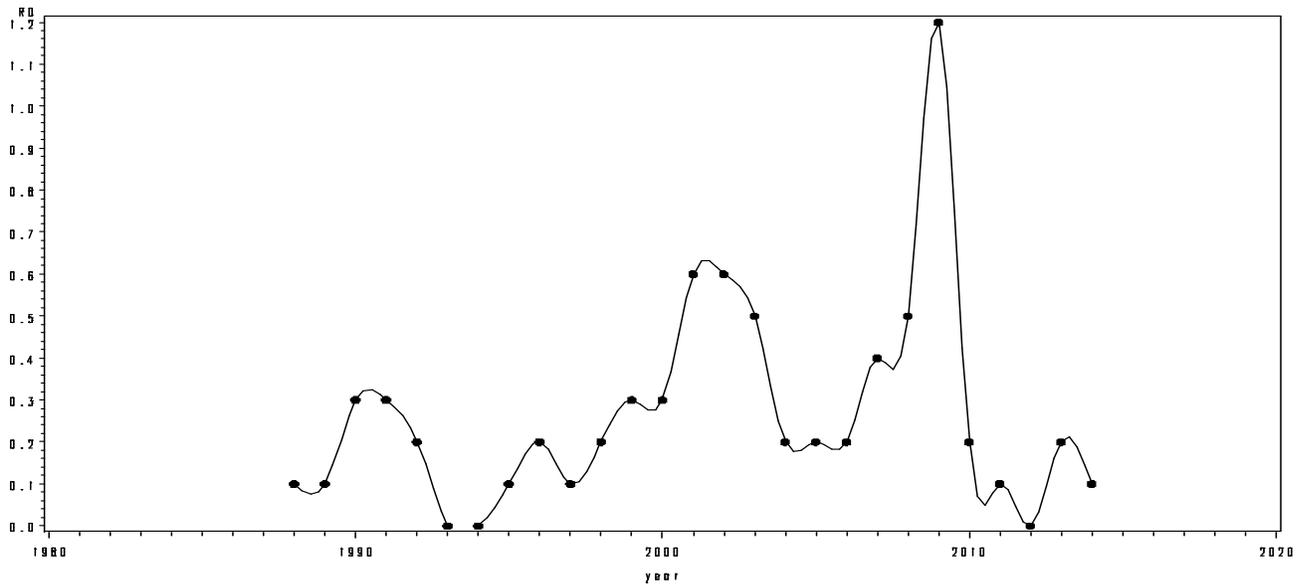
**FIGURE 2. PLOT OF PERCENT CHANGE FROM YEAR AGO OF RESEARCH AND
DEVELOPMENT (RD) IN MANUFACTURING OVER YEARS**

GDP Per Hour Worked

GDP per hour worked used as the input variable in Equation (1) had no significant effect on employment as the output variable.

GDP Per Capita

The GDP per capita (Figure 3), differenced once, was related to employment in manufacturing (on a quarterly basis) through the equation:

$y(1,4)_t = -42.89 + (0.183\ x(1)_t - 0.093\ x(1)_{t-1})/(1 - 1.54B + 0.85B^2) + (1 - ,65B^4)\ e_t/\ (1-0.46B)$ (4)

Here, y = employment in manufacturing, x is the GDP per capita, B is the Backshift operator, and e is random error. $y(1,4)_t$ was differenced at lags 1 and 4 for stationarity and $x(1)_t$ was the first difference.

All coefficients in Equation (4) were highly significant (P< 0.001). Only the p value was 0.066 for the estimate 0.093. In order to determine the relationship between x and y, we multiply $(0.183\ x(1)_t - 0.093\ x(1)_{t-1})$ by (1-.46B) and simplify to obtain the expression
$0.183\ x(1)_t - 0.177\ x(1)_{t-1} + 0.0428\ x(1)_{t-2}$ It is seen that with past values $(x(1)_{t-1}$ and $x(1)_{t-2})$ fixed, employment in manufacturing (y_t) is positively related to a change in GDP per capita $(x(1)_t)$ One

can conclude that if improvement in technology works to reduce employment, then GDP per capita is not a good measure of technology, since it is positively correlated with employment.
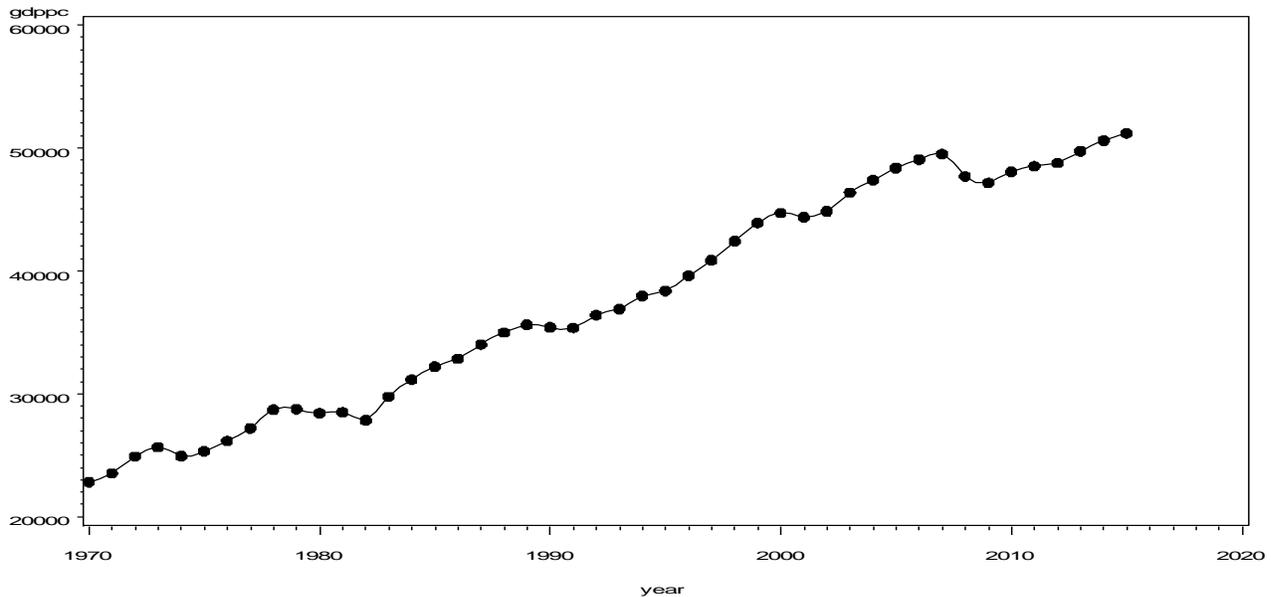

FIGURE 3. PLOT OF GDP PER CAPITA IN DOLLARS (GDPPC) OVER YEARS

Labor Productivity

When labor productivity data (Figure 4), differenced once, was used as the input variable in Equation (1) and employment (on a quarterly basis) as the output variable, the relationship was shown to be:

$y(1,4)_t$ = -37.36 + 33.75 $x(1)_{t-1}$ / (1-1.108 B + 0.699B^2) + (1 − 0.633 B^4) e_t /(1 − 0.671B)   (5)

All the coefficients in Equation (5) were highly significant ($p < 0.001$).

The relationship between x and y can be revealed by multiplying 33.75 $x(1)_{t-1}$ by /(1 − 0.671B) and simplifying to obtain the expression 33.75 x_{t-1} − 56.4 x_{t-2} + 22.65 x_{t-3}. With x_{t-2} and x_{t-3} fixed, employment (y_t) is positively related to labor productivity (x_{t-1}).

Hence, an increase in labor productivity will increase employment in manufacturing (The effect manifests itself after a one quarter lag or delay) This is contrary to expectation if labor productivity is a true measure of technological change, which has been proposed to be negatively related to employment.
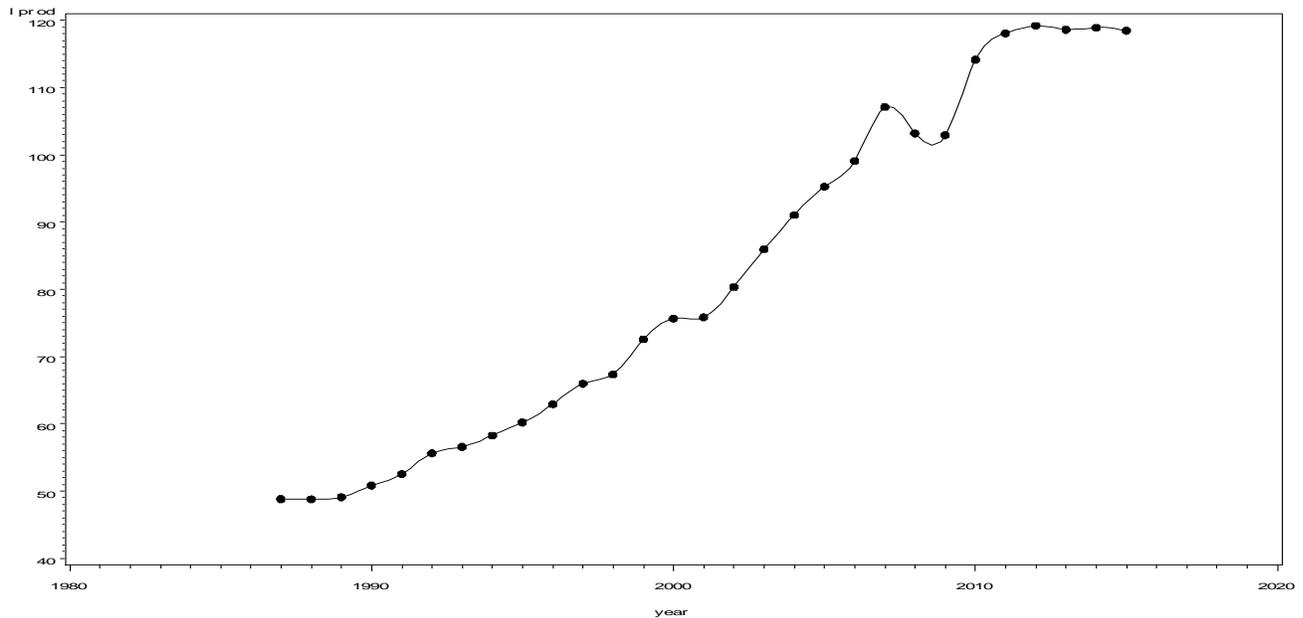
FIGURE 4. PLOT OF LABOR PRODUCTIVITY OVER YEARS

Total Factor Productivity (National Level)

The relationship of the input series, total factor productivity (Figure 5), differenced once, and the output series employment in manufacturing (on a yearly basis) was identified as:

$$y(1)_t = -383.27 + 39310.3\ x(1)_t + e_t/(1-.51B) \tag{6}$$

It is clear from Equation (6) that there is a positive relationship between total factor productivity and employment in manufacturing. Multiplying $39310.3\ x(1)_t$ by $(1-.51B)$ and simplifying, one obtains the expression $39310.3\ x_t - 59358.55\ x_{t-1} + 20048.25\ x_{t-2}$.

As can be seen, an increase in total factor productivity at time t (x_t) (with x_{t-1} and x_{t-2} fixed) will increase rather than decrease employment. This indicates that total factor productivity is not a good measure of technological change, assuming that an increase in technology would have a negative effect on employment.
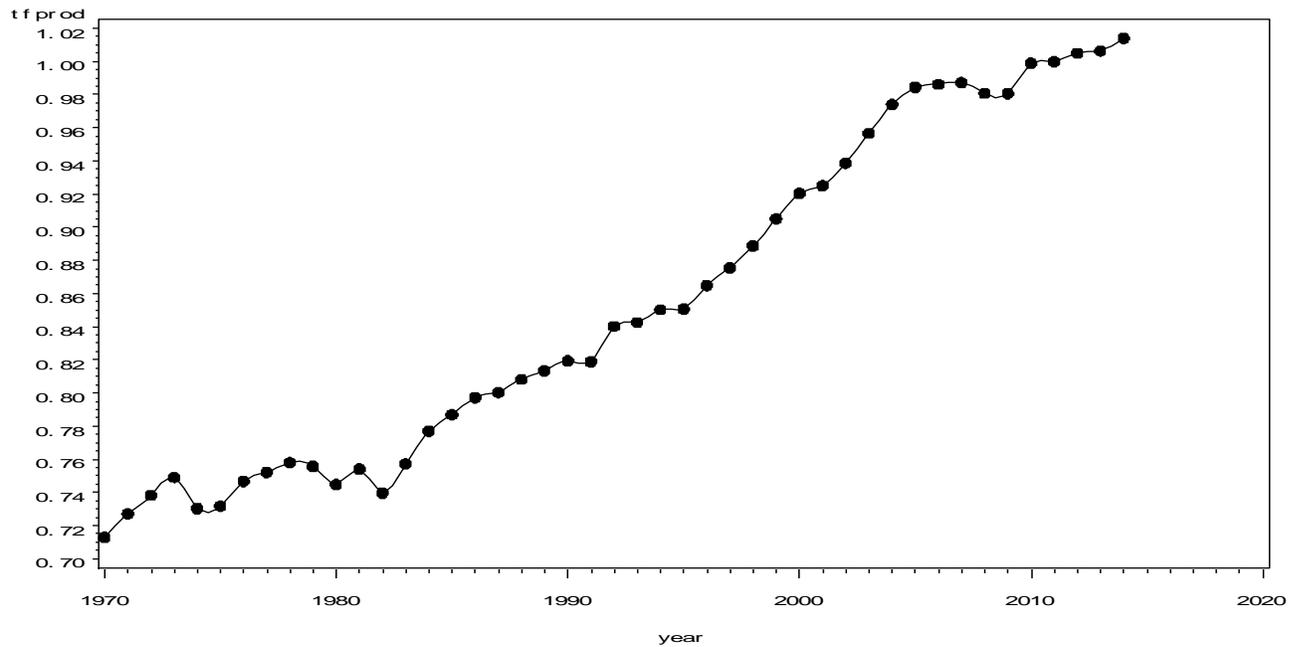
FIGURE 5. PLOT OF TOTAL FACTOR PRODUCTIVITY IN THE US (TFPROD) OVER YEARS

Total Factor Productivity in Manufacturing

The total factor productivity in manufacturing as the input series x (measured as percent change from the year before, Figure 6) was related to employment in manufacturing y (on a yearly basis) as follows:

$$y(1)_t = 122.97 \, x_t + e_t/(1-0.783B) \tag{7}$$

The coefficients in (7) were highly significant (p< 0.001).

Multiplying $122.97 \, x_t$ by $(1-0.783B)$ and simplifying, one has the inequality $122.07 \, x_t - 96.28 \, x_{t-1}$. This shows that an increase in total factor productivity at time t (x_t) (with x_{t-1} fixed) will increase employment in manufacturing. This is contrary to expectation if total factor productivity is a good measure of technology.
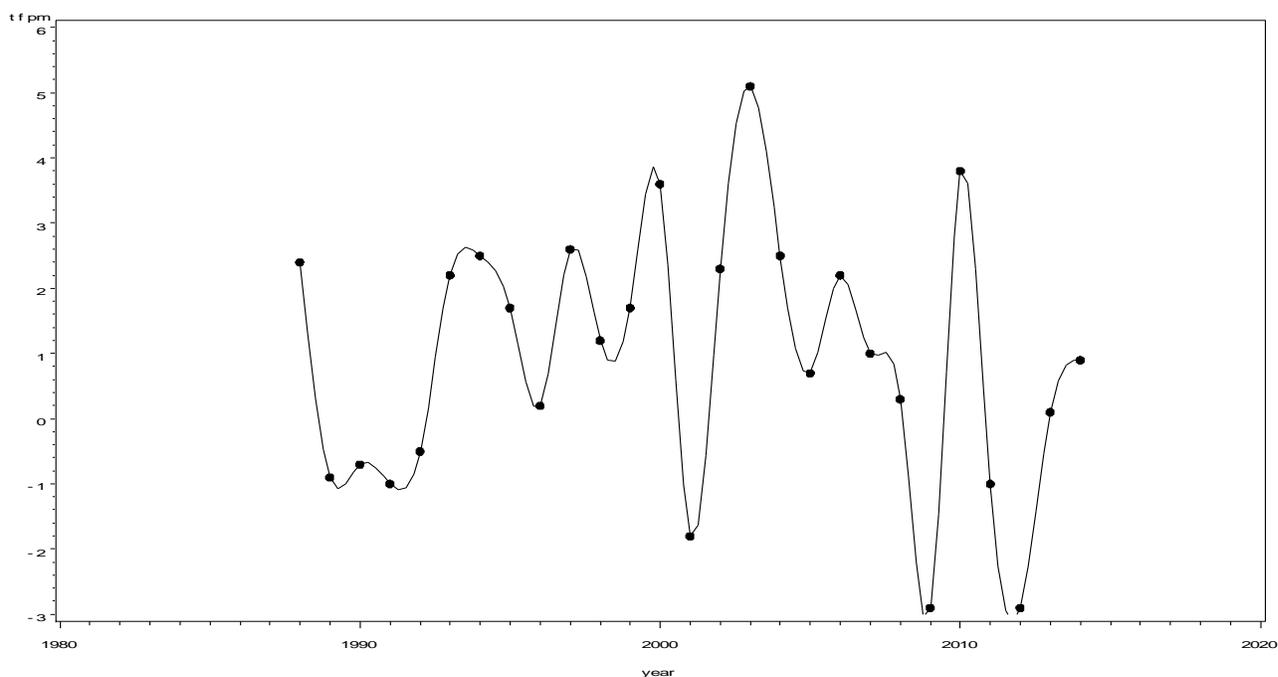
FIGURE 6. PLOT OF TOTAL FACTOR PRODUCTIVITY IN MANUFACTURING (TFPM) OVER YEARS

DISCUSSION

It is seen from this time series analysis that labor productivity, total factor productivity, and GDP per capita all have a positive effect on employment in manufacturing. Only Research and Development in the manufacturing sector had a negative effect on employment in manufacturing.

Graham (2016) pointed out that technological change is not the only factor that changes labor productivity and total factor productivity. For instance, since labor and total factor productivity are both based upon the amount of input and the quantity of output produced, change in input prices will have an effect on changing labor and total factor productivity. Viewed as such, labor productivity and total factor productivity (the two factors mostly used as measures of technology) may not be true measures of technological change. Our analysis showed that both measures are positively (rather than negatively) related to employment.

From this analysis, it seems that, from all the measures investigated, the only true measure of technological change is R&D in the manufacturing sector. It is clearly shown that an increase in R&D in manufacturing has the effect of reducing employment in manufacturing. This is in agreement with expectations, and with some of the studies in the literature, namely Brynjolfsson and McAfee (2011) and Mullen et al. (2009). Research and development can translate into investment in automation and information technology, which can have a negative effect on employment. It is of interest to note that R&D for industry as a whole had no relationship with

employment in manufacturing. This suggests that one should consider R&D for the sector under consideration as a measure of technological change for that sector.

CONCLUSION

Technological change in a country has an impact on its economy and affects employment in manufacturing. Different technological measures were used in the literature in order to study their relationships to employment. Results are mixed as to how each measure may relate to employment in manufacturing. In this study we use the transfer function time series modeling approach where an output series (employment in manufacturing) is related to an input series (technology measure). The measures considered are those proposed in the literature, namely labor productivity, total factor productivity (TFP), GDP per capita, GDP per hour worked, and research and development (R&D) in manufacturing. Results from the analysis revealed that only R&D in manufacturing had a negative and significant effect on employment in manufacturing. GDP per hour worked was not related to employment and all the rest of the measures above were positively related to employment in manufacturing. If improvement in technology decreases employment in manufacturing, then a true measure of technological change is R&D in manufacturing and not any of the other proposed measures.
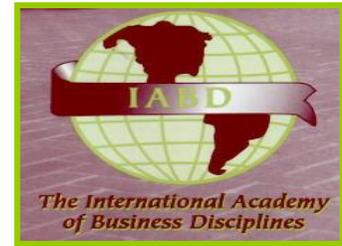
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