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The Media is the Measure: Technical change and employment, 1909-49

By Michelle Alexopoulos and Jon Cohen

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Michelle Alexopoulos* and Jon Cohen

University of Toronto

*Contact information: Department of Economics, University of Toronto, 150 St. George St., Toronto, ON, M5S 3G7. e-mail: malex@chass.utoronto.ca

Abstract

Difficulties in sorting out the empirical relationship between technical change and employment is attributable, at least in part, to the shortcomings associated with traditional measures of the former. In this paper, we use new indicators of technical change that we believe resolve many issues associated with other methods of identifying technology shocks, and use them to explore the impact of technical change on employment from 1909-49. The payoff to this effort is substantial for at least three reasons. First, it sheds light on the role of technology shocks in cyclical fluctuations during this period, second, it informs business cycle model selection (New Keynesian vs. Real Business Cycle), and, third, it contributes to our understanding of the part played by the New Deal Policies in the recovery from the Great Depression.

Keywords: Business Cycles; Technical Change; Great Depression; Unemployment

JEL: E2, E3, N1, O3

I. Introduction

In this paper, we employ a new indicator of technological change to identify the relationship between technology shocks and employment in the U.S. for the period 1909-1949. We are motivated by a number of considerations. First, the empirical relationship between technology shocks and employment is a hotly debated topic among macroeconomists. The reason for this is simple. Different business cycle models make very different predictions about the impact of technology shocks on employment – the real business cycle (RBC) theorists claim that it is positive, the new Keynesians that it is, at least initially, negative[1]. The results of empirical studies that attempt to uncover what happens following technology shocks are, therefore, likely to affect both model selection and the assessment of the role of real shocks in cyclical fluctuations.[2] Second, although most efforts to date have concentrated on the post-World War II years, a larger number of business cycles occurred during the first half of the twentieth century, including, of course, the most severe depression ever recorded. In other words, the period is ideal for a study of this sort. Third, Roosevelt and many in his administration believed that technical change contributed to the high rates of unemployment during the 1930s. Finally, by examining the predicted response of employment to technology shocks for this period, we may be able to help determine which of the two benchmark models, neoclassical or new Keynesian, provides the best approximation of the underlying economy, an outcome with important implications for policy debates.

One policy issue that has received considerable attention in recent years is the role played by the National Industrial Recovery Act (NIRA) in the economy's recovery from the Great Depression. Cole and Ohanian

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[1] As noted by Christiano, Eichenbaum and Evans (2004), this outcome depends on the assumption that the monetary authority does not accommodate the technology shock. A sticky price model with accommodation does not have the negative response to technology shocks.

[2] See Christiano, Eichenbaum and Vigfussion (2003) and Fisher (2006) for empirical results that support the RBC view and Gali (1999), Gali and Rabanal (2004), Basu, Fernald and Kimball (2006) for evidence in favor of the new Keynesian model.

(1999, 2004), for example, contend that the NIRA transformed an essentially neo-classical economy with competitive product and factor markets into one with cartelized firms and enhanced labor bargaining power. The consequence of this intervention was, ironically, slower than expected economic growth and anemic job creation after 1933. Eggertson (2006), on the other hand, has argued that if the benchmark economy in the 1930s was of the new Keynesian variety with sticky prices, then New Deal policies, including the NIRA, may have been optimal - given that the economy was, at the same time, being hit with deflationary shocks and the monetary authority was constrained by the zero bound on interest rates. The question, of course, is which of the two is correct, and the answer, in part, relies on which of the two models – neoclassical or new Keynesian- provides the best approximation of the economy prior to the interventions associated with the New Deal? Sorting out the empirical relationship between technical change and employment will help us answer this question.

Although most would agree that technical change does have an impact on employment opportunities, there is much less unanimity about the nature of this relationship, in large part because we lack a compelling measure of the former.[3] All the usual indicators including patents, research and development expenditures, and identifying restrictions in vector autoregressions have been used in empirical studies of the post-WW II period in an effort to tease out this link but, due to the well known shortcomings of each, the results based on them remain inconclusive.[4] Thus, whereas Gali (1999), Francis and Ramey (2005, 2004), and Gali and Rabanal (2004) claim that hours worked decline, at least in the short run, in response to a positive technology shock, Christiano, Eichenbaum, and Vigfusson (2003), and Fisher (2006) contend, using the same identifying assumptions, that the evidence, such as it is, leads to the opposite

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[3] See, among others, Griliches (1990), for a review of some of these issues.

[4] Gali (1999), Francis and Ramey (2005), Christiano et al. (2003) and Fisher (2006) identify technology shocks by using a long-run identifying assumption in a VAR (namely only technology shocks affect labor productivity in the limit). Basu, Fernald, and Kimball (2006) argue that their cleansed Solow residual can serve as a reliable proxy for technical change, while Shea (1998) uses information on patents and R&D expenditures to identify technology shocks.

conclusion.[5] Basu, Fernald, and Kimball (2004), relying on a cleansed Solow residual, find a decrease in hours worked following a positive technology shock, while Christiano, Eichenbaum and Vigfussion (2004) argue that these findings are attributable to measurement error. Finally, Shea (1998), using patents and R&D statistics, comes up with inconclusive results (largely because he finds that his proxies have almost no impact on measured TFP). In a nutshell, then, while a compelling measure of technical change may be hard to find, it is certainly worth looking for, since it is likely to help us answer the key question – what does happen to employment following a technology shock?

We use in this paper, new and, we believe, relatively problem-free, indicators of technological change for the pre-WW II to estimate the impact of new technologies on employment.[6] They are based on data taken from the Library of Congress (LC) on the number of new technology titles in various fields published in the United States during the first fifty years of the last century. They have a number of attractive features. They are objective, unlike innovations counts, they isolate pure technological innovation unlike traditional productivity statistics, and they capture innovations at the moment of their commercialization, unlike patents and research and development outlays. Finally, because the LC data can be used to create a consistent times series of innovative activity on an annual basis for the entire period 1909-1949, both for technology in general and for various sub-groups, they can be employed to estimate statistically the impact of unanticipated changes in technology on employment. Although the results may not fully settle the controversies, they will advance our understanding of the interaction between new technologies and employment opportunities.

[5] The two groups of researchers make different assumptions about the stationarity of the log of per capita hours worked. The first group assumes that the first difference is stationary, while the second argues that the log series itself is stationary.

[6] See Alexopoulos (2006) and Alexopoulos and Cohen (2008a, 2008b) for further discussion of these indicators, and Alexopoulos (2006, 2007) for a similar exercise focusing on the post WWII period.

To summarize briefly our results, our point estimates do indicate a positive relationship between general technology shocks and employment in the short and medium runs.[7] Among subgroups, we find that: (1) innovations in the automotive, mechanical, and electrical sub-sectors had the largest impacts on productivity, and (2) changes in electrical and automotive technologies tended to increase employment in a variety of sectors while other subgroups of technologies seem to have had little or no impact.

These findings are of interest for a number of reasons. First, although we use a different measure of technological change than that employed by Francis and Ramey (2004), our findings are strikingly similar to theirs for this period. Second, we find that over the entire period, even if there were frictions and/or wage and price rigidities in some sub-sectors of the economy, they were insufficient to offset the positive impact of technical change on employment (primarily related to changes in electrical and automotive technologies). Third, our data and approach permit us to pinpoint the spillover effects of sector specific new technologies on the broader economy, effects often missed by detailed sector studies such as those of the National Research Project.[8]

Finally, our data indicate, in keeping with the findings of Field (2003), Mensch (1979), Kleinknecht (1987), and Bernstein (1987), that the 1930s, especially the period 1934-41, was a time of rapid technological progress. In the best of all possible worlds – that is, one approximated by neoclassical market conditions – this should have led to rapid growth in output, productivity, and employment, none of which, in fact, occurred. As noted, Cole and Ohanian (2004) attribute this failure to New Deal policies.[9] In an attempt to see if our results are sensitive to the peculiarities of these years, we remove them from our

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[7] Although we focus on the relationship between technical change and employment, it is also likely that the type of technical change we identify had a significant impact on wages and overall wage inequality. See Barlevy and Tsiddon (2006).

[8] This tendency of sectoral studies to overlook the forest for the trees is precisely the shortcoming identified by Cyert and Mowery (1987, pp. 93-94).

[9] Bernstein (1987) and Hawley (1964), among others, argue that the NIRA and related New Deal policies contributed to the sluggish growth of output and jobs after 1934.

regressions by including dummy variables for the years 1934-9. As it happens, our findings are not altered significantly by this change. Since we do find, overall, a positive relationship between technology shocks (based on our new indicators) and productivity and employment, we would have expected to see, in keeping with Cole and Ohanian (2004), a more robust recovery in job creation. Questions about the wisdom of New Deal policies, therefore, remain.

We proceed as follows in the remainder of the paper. In the next section, we review some of the related literature, describe our indicators, review their intuitive appeal, and present the data we need for our regressions. In section three, we report and discuss our regression results. In section four, we focus sharply on the depression years and demonstrate first that even in the absence of the NIRA and related policies, unemployment would have remained high and, second, speculate about other causes of the slow recovery. In section five, we summarize our findings and identify areas for future research.

II.1 Other Related Literature on Technical Change and Employment

The idea that machines replace men has a long, if not entirely distinguished, history going back at least to the machine breakers of the early industrial revolution. The creation of the U.S. Bureau of Labor (subsequently the Department of Labor) in 1884 represented, in large part, a response to labor leaders' concern that machines were replacing skilled operatives. In its first report, published in 1886, the Bureau observed that "…mechanization was the essential reason for the unemployment characteristic of depression."

The 1920s and especially the 1930s marked a high point in the public's preoccupation with labor displacement. Anecdotal but nevertheless compelling evidence of this can be seen in Figure 1, in which the number of New York Times articles using the phrase 'technological unemployment' is reported by decade between 1920 and 1979. As can be seen, between 1920-29 13 articles appeared, between 1930-39 the number jumped to 355, in the following decade the number dropped to 63, and, in the post-war decades, the number ranged from a low of 10 between 1970-79 and ***a*** high in the previous decade of 61. Although the 1930s were, clearly, special, it is worth noting that concern over the perceived tendency of machines to replace workers was accelerating in the years prior to the Great Depression. [10] In Figure 2 we present two graphs published in a February 1928 New York Times Article entitled, "March of the Machine Makes Idle Hands". Three main observations were made in the article. First, starting somewhere around 1919, the data indicate that fewer workers were required to produce a unit of output in the manufacturing sector. Second, this trend started even earlier in the agricultural sector, and, third, the increase in productivity resulted from the introduction of new machines. Technological change was, in short, the evil genius responsible for idle hands.

This view coincided with that of Roosevelt and many in his administration that technological change was displacing labor. At a 1935 press conference, the President stated that even if the nation could immediately restore production to its 1929 level "…the rebound would supply jobs for only about 80 percent of the unemployed, because mechanization had so profoundly increased capital efficiency…"[11] In his 1940 State of the Union address, he retuned to this theme: "While the immediate number of unemployed has decreased, while their immediate needs for food and clothing…have been met…we have not yet found a way to employ the surplus of our labor which the efficiency of our industrial processes has created." [12]

In 1935, Harry Hopkins, head of the Works Progress Administration (WPA), sponsored the National Research Project (NRP) to look into the impact of recent changes in industrial techniques across a wide

[10] These results raise an obvious question. Does the trend represent no more than increased use of the term 'technological unemployment' or does it, instead, reflect a growing concern about this phenomenon? To answer this question, we also examined the pattern of articles published in the New York Times that contained related keywords such as 'displaced workers', 'technical change', and 'technology'. All these variations we tried yielded a similar pattern, a clear indication that there was a large increase in these types of articles in the 1930s.

[11] See Bix (2000).

[12] See Israel (1967).

range of sectors – including agriculture - on unemployment and employment. The project was motivated explicitly by the conviction that unemployment was attributable to the substitution of machines for men. Henry Wallace, Secretary of Agriculture and later Vice-President, used words almost identical to those of the President to describe the impact of technological change on employment: "The production of our factories is nearing normal, but the number of unemployed remains unusually large. It is apparent that many of our unemployed may never get jobs again. Machines and younger people have taken their places."[13]

The notion has continued to thrive in the post-WW II period. Cyert, in his preface to a 1987 report dealing with the impact of technological change on employment and productivity, notes that many Americans believe that new technologies are more likely to destroy than to create jobs – as it happens, contrary to conclusions of the report.[14] A few years later, the idea surfaced again and many journalists reported that we had entered a "new era" in which rapid productivity growth was likely to be associated with permanent labor displacement.[15] Indeed, Kahn (1993), in an article titled, "Sluggish Job Growth: Is Rising Productivity or an Anemic Recovery to Blame?," maintains that there is evidence to support the idea that computer technologies and business restructuring contributed to both the rising productivity and weak recovery in employment from the 1991 recession. In 2004, a special report appeared in Business Week entitled "The Price of Efficiency." In the report, it was pointed out that demand for goods was the strongest in years, profits were robust, business investment was surging, and yet employers were not hanging out help wanted signs. The job killer was the dramatic gains in productivity linked to new technologies that allowed businesses to expand output without increasing employment. King Ludd, it would seem, remained alive and well.

[13] Quoted in Bernstein 1987, p. 145, taken from a book Wallace published in 1937 entitled *Technology, Corporations, and the General Welfare*.

[14] See Cyert and Mowery (1987).

[15] See, for example, articles by A. Ehrbar, D. Wessel, and W. Bulkeley, in the Wall Street Journal.

The prime mover in the public's perception is obviously technological change – and herein lays the problem. To identify the impact of technology and technology shocks on output and employment, we require an indicator of innovative activity that is quantifiable, consistent over time and across sectors, objective, and able to capture new technologies at the moment of their commercialization. In the next section, we discuss new measures of technological innovation that, we believe, satisfy these criteria and then use them to explore the relationship between employment and technical change.

II. 2 Data

A. Employment and Productivity

Before we discuss our new indicators, we briefly review the data on employment and unemployment that we use for our analysis. Since there are no official series produced for the early part of our sample, we are compelled to fall back on standard ones used by others for this time period. We rely on data from Kendrick (1961) for output per worker in the private non-farm economy as well as for the manufacturing and transportation sectors. Data for aggregate employment and for the aggregate unemployment rate are taken from the *Historical Statistics of the United States Millennial Edition* (Table Ba 470-477). GNP per person (in 1929 and 1947 constant dollars) comes from the Economic Almanac of the National Conference Board while Solow (1957) and Goldsmith (1956) are the sources for data required to compute TFP for the private non-farm economy.[16]

As the discussions in Solow (1957) and Kuznets (1961, pp. 505-510) illustrate, productivity and growth rate estimates are often sensitive to the choice of base year and using deflators with a base year closer to

[16] Our TFP series are calculated using the equation:

$$\frac{\Delta TFP}{TFP} = \frac{\Delta\left(\frac{GNP}{L}\right)}{\left(\frac{GNP}{L}\right)} - \omega_K \frac{\Delta\left(\frac{K}{L}\right)}{\left(\frac{K}{L}\right)}$$

, where GNP is private non-farm GNP, L is the number of hours worked, K is the capital stock, and ω_K is Solow's (1957) share of property in income.

the end of the period investigated are preferable –especially during times when there are rapid changes in technology and in the types of goods available in the economy. Although it is possible using data from the Economic Almanac to calculate both GNP per person and aggregate productivity in 1947 constant dollars, the only sectoral level data available comes from Kendrick (1961) and are in 1929 constant dollars. The problem for us is that data are likely to cause us to underestimate the relationship between technical change (as measured by our indicators) and productivity. [17] In an attempt to evaluate the severity of this underestimation, we report below two sets of results, one for GNP per person and aggregate TFP based on data corrected with Kendrick's (1961) base year 1929 price deflator, the other adjusted using the 1947 deflator (also created by Kendrick) from the Economic Almanac.

We present in Figures 3 and 4 trends in employment, unemployment and productivity for the entire period. A few features of the graphs are worth highlighting. First, unemployment jumped sharply in the 1930s. As the numbers suggest, the drop in employment was seen across a wide variety of sectors including manufacturing and transportation. Second, while the 1930s did witness a large decline in productivity, the decline was limited to the early years. By 1934 productivity was on the road to recovery and by the end of the decade it was booming. In fact, according to Field (2003) and Mensch (1979), this decade was one of the technologically most progressive of the last the century.

B. Indicators of Technological change.

For our purposes, we require an indicator of technical change that captures an innovation at the moment of its commercialization for the obvious reason that it is only through its adoption that it affects the demand for labor. All of the usual suspects fail to meet this requirement. Research and development expenditures measure inputs into the inventive process not outputs of commercially viable innovations.

[17] The downward bias can be attributed both to the changes that occurred between the beginning and the end of the decade in the availability and measurement of prices, and in the weights assigned to goods and services in the different price indexes. Kendrick (1961), who uses numbers expressed in constant 1929 dollars, acknowledges that there is a large degree of measurement error in his 1929 deflators and also recognizes that the choice of the base year could affect his productivity estimates. He does not experiment with alternatives in his well known book.

Patent applications and/or grants do represent potentially valuable new additions to economic knowledge[18] but the long and uncertain lags associated with their commercial adoption make them at best imperfect indicators. Although innovation counts resolve some of these problems, they are difficult to quantify and are notoriously subjective.[19] Finally, while changes in productivity numbers (even those cleansed using techniques proposed by Basu, Fernald, and Kimball (2006) or Ohanian (2001)) do pick up changes in efficiency, they are influenced by factors other than technical change, such as, for example, changes in regulations.

Given the problems associated with the traditional indicators, we chose, instead, to use publication-based measures presented in Alexopoulos and Cohen (2008a) for total, manufacturing and mechanical, electrical (including telecommunications), and automotive technologies and to construct using the same procedures a new set of publication-based indicators for railroad technology. Following the methodology proposed in Alexopoulos (2006), they were created using the Library of Congress' MARC (MAchine Readable Cataloguing) record database. They are ideal for our purposes. First, as Alexopoulos and Cohen (2008b) demonstrate, the measures satisfy the timing requirement.[20] Second, the indicators are based on the huge collection of the printed materials held by the Library of Congress, over 130 million items in more than 450 languages, which, among other things, provides a virtually complete list of all new technology titles published and copyrighted each year in the United States. They are, therefore, likely to capture the full array of new technologies that appeared during this period.[21] Third, and related, our

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[18] See Griliches (1990).

[19] See Cyert and Mowery (1987), Griliches(1990), Alexopoulos and Cohen.(2008b).

[20] Case studies in Alexopoulos and Cohen (2008b) reveal, first, that these indicators represent innovation not diffusion and, second, that the appearance of new titles corresponds closely with the commercialization date of the innovation. See also Alexopoulos and Cohen (2008a).

[21] Although the LC, as the country's principal depository library, receives notification of all new titles copyrighted in the U.S., it is not obliged to hold a copy of each publication. Its holdings are, nevertheless, vast – probably the most extensive in the world – and are certainly adequate for our purposes. See John Y. Cole, Jefferson's Legacy: A Brief History of the Library of Congress, http://www.loc.gov/loc/legacy/.

indicators pick up not just new product innovations but also those associated with new practices in management and organization for the obvious reason that someone stands to profit by writing about them. These are rarely, if ever, captured by patents or research and development outlays.[22] Fourth, the publication series weight the various new technologies differently - a potentially important factor when trying to identify the impact of innovations on output and employment. That is, since more titles are likely to appear on major technologies than on minor ones, our indicators, by their very nature, give greater weight to major than to minor innovations. If, as we suspect, the former are likely to have a greater impact on employment opportunities than the latter, our indicators will flag this effect. Fifth, as Alexopoulos and Cohen (2008a) demonstrate, there is little reason to assume that the observed pattern merely represents trends in publishing.

The indicators, chosen to correspond with our sectors (total private non-farm, manufacturing, and transportation) are displayed in Figure 6. A few features of these graphs are worth highlighting. First, they indicate that the 1930s was a technologically progressive decade, especially the second half when productivity was also rising rapidly. Second, the patterns traced by all new technology titles and by the technology sub-groups differ. Thus, new publications in electrical engineering undergo a sharp drop between 1929 and 1932 but then recover nicely through 1941. On the other hand, manufacturing technology titles begin their recovery from the Depression in 1933 and continue with ups and downs through 1942. Third, there are distinct differences across sub-groups during the war years, a consequence of restrictions placed on the civilian activities of some of these groups such as automotive. We can draw the following inferences from these observations. First, they suggest that our indicators do represent group specific changes in technology and are not mere artifacts of the publishing industry. Second, it is likely that the impact of the new technologies on aggregate employment differed across sub-groups.

III. Exploring the relationship between employment and productivity

[22] In our time period, there is evidence that changes in management techniques and the organization of production also had a considerable impact on productivity. (See Weintraub (1939))

III.A. The link between the indicators and productivity

It is necessary, before we consider the effects of technical change on aggregate employment and employment in the manufacturing and transportation sectors, to show that our measures of technical change affect productivity at both the aggregate and sectoral levels. Although similar to the analysis in Alexopoulos and Cohen (2008a), we present in this paper results based on different productivity series for the aggregate economy. Specifically, we consider the responses of both TFP and output per worker measures and, as noted earlier, examine both the set of measures created using Kendrick's 1929 price deflators, and the set calculated using data deflated with the 1947 index. In addition to presenting findings at the aggregate level, we expand our analysis to include productivity measures for both the manufacturing and transportation sectors. To be more precise, we explore the relationship between technological change (as measured by our indicators) and output/worker and TFP by estimating the following bi-variate VARs:

$$Y_t = \alpha + \gamma_0 t + \gamma_1 t^2 + \rho Y_{t-1} + \varepsilon_t \qquad (1)$$

where $Y_t = [\ln(Z_t), \ln(X_t)]'$, with Z_t being our measure of output per worker or TFP, and X_t is one of our technology indicators (total, manufacturing and mechanical, electrical and electronic, automotive, or railroad).[23] As in Shea (1998) and Alexopoulos (2006), we identify technology shocks by assuming that they affect the Z variables with a one year time lag.[24] Table 1 reports the point estimates on lagged productivity and the lagged technical change measure (as well as the associated standard errors) for the productivity equation. The first four rows contain the results when the total technology indicator and the subgroup indicators (manufacturing and mechanical, electrical and electronic, and automotive

[23] Due to the short time series available, the unit root tests are inconclusive. Therefore, we opt to use levels instead of first differences and include a quadratic time trend.

[24] We also ran the VARs with the technology indicator entering before our productivity variables to see if a change in ordering affected our results. We found little evidence to suggest that it mattered. These results are available upon request.

technologies) are used, while the fifth row highlights the relationship between technical change in railroads and productivity in the transportation sector (since we would expect to observe an impact of the former on the latter).

Figure 7 displays the impulse responses of GNP per worker (in 1929 and 1947 constant dollars), and Figure 8 shows the responses for output per worker (in 1929 dollars) and TFP for the private non-farm economy to a one standard deviation technology shock (as identified by our indicators), and 90 percent confidence intervals.[25] A few findings are worth emphasizing. First, the point estimates suggest that both TFP and labor productivity increase following a technology shock. Second, automotive shocks appear to have the longest significant impact, while the effects of electrical and electronic technologies are the most rapid. Third, the choice of price deflator matters. In particular, we find that the productivity measures computed using the 1947 deflators are much more responsive to changes in technology than those based on the 1929 deflators. These results confirm Kendrick's (1961) warning mentioned earlier that his 1929 deflators are subject to a fair degree of measurement error, caused in part by the total absence of price data for some goods, such as durable equipment, in the early years. In addition, these findings suggest that the magnitudes of the relationships at the industry level (which, by necessity, are based on 1929 constant dollar data) are likely to be biased downwards.

Figure 9 presents the impulse responses of output per worker for the manufacturing and transportation sectors. The results are similar to those seen at the more aggregate level. Although the standard errors are a little larger (a consequence, perhaps, of measurement error in the 1929 deflators), the

[25] Francis and Ramey (2004) use the long-run restrictions approach in a VAR to identify technology shocks in the pre-WWII period and to determine the response of aggregate hours per capita to these shocks. Their results are similar to the ones reported here.

overall point estimates indicate that the relationship between labor productivity and our measures of technical change are positive for these industries.[26]

The results of the Granger Causality tests and the variance decompositions, shown in Tables 2 and 3 respectively, confirm that there is generally a statistically significant relationship between our productivity measures and our indicators. Moreover, for the aggregate economy and the private non-farm economy, we find that manufacturing, electrical and automotive technologies had the largest impacts. Using the productivity measures computed using data deflated with the 1947 price indexes, we find that, at a six year horizon, over 40 percent of the variation in GNP per worker, and 30 percent of variation in TFP in the private non-farm sector, can be explained by changes in mechanical technologies. Electrical technologies had the largest (and most significant) impact on output per worker in the manufacturing sector, while new automotive technologies explained over 20 percent of the variation in output per worker in transportation.

III.B. The link between employment, unemployment, and technical change

We turn now to the primary objective of this analysis: to identify the relationship, if any, between our indicators of technical change and employment/unemployment during this period. To do this, we estimate a set of bi-variate VARs similar to those described in the previous sub-section. Specifically we assume that the relationship between technical change and employment (or unemployment) can be represented as:

$$Y_t = \alpha + \gamma_0 t + \gamma_1 t^2 + \rho Y_{t-1} + \varepsilon_t \qquad (1)$$

where $Y_t = [\ln(Z_t), \ln(X_t)]'$, with Z_t being our measure of employment per capita, hours per capita or the unemployment rate, and X_t is one of our technology indicators.[27] Table 4 presents the point estimates and

[26]It is useful to note that the time series for manufacturing and transportation are only available in 1929 constant dollars. This may very well account for the relatively large standard errors.

[27] Again we use log levels and include a quadratic time trend. Francis and Ramey (2004) also find that the quadratic trend captures the trend in per capita hours worked for this period.

standard errors for these regressions, while Tables 5 and 6 display the Granger-causality tests and the variance decompositions.

We find no evidence that the technology shocks significantly decreased employment (or increased unemployment). Instead, our results indicate that, on the whole, employment opportunities went up following a positive technology shock – even in the short run. The point estimates for total technical change suggest a positive relationship at both the aggregate and the disaggregate levels, and in the case of manufacturing employment, the response to a 'total technology' shock may be viewed as weakly significant.

The findings are stronger for the various technology sub-groups. Overall, we find that electrical and automotive technologies seem to have to led to significant increases in employment (and decreases in unemployment) at the aggregate and disaggregate levels. In fact, of all the major sub-groups considered, only new manufacturing/mechanical technology failed to have a large, positive impact on all of the employment/unemployment series.

The results for manufacturing/mechanical technologies are actually very interesting when considered in light of the observations contained in the National Research Project reports for these groups. In a number of instances, while it is acknowledged that innovations in mechanical machinery did seem to displace workers at the firm level, the authors of the reports argued that care needed to be taken when extrapolating the results of the cases studies to an aggregate level. They point out that while employment in some occupations may have fallen as machines replaced men, the narrowly focused studies fail to pick up the positive effects on employment created by the demand for labor to build the new machines, to repair them, and so on. There were, in short, two effects on employment of advances in this area, one positive, the other negative. One interpretation of our results is that the two forces may very well have cancelled each other out.

The variance decompositions echo these findings and indicate the importance of each type of technical change in explaining the variation in employment/hours and the unemployment rate. For the most part, the results using the total technology measure suggest that these shocks are able to account for only a small percent of the variation in employment. On the other hand, based on our identifying assumptions, zero percent of the variance is explained by our technology indicators in year one but we do find that, over time, the percent explained goes up, especially for those linked to automotive and electrical technologies. Of the different sub-groups, changes in automotive technologies had the largest impact. In particular, they account for almost 30 percent of the variation in manufacturing employment, and almost 20 percent of that in the aggregate unemployment rate at a six year horizon. In contrast, for the same time horizon, electrical technologies account for close to 11 percent in non-farm per capita hours and per capita employment in manufacturing, and approximately 12.5 percent of the variation in the unemployment rate. Mechanical/manufacturing technologies only had a significant impact on employment opportunities in the transportation sector (where over 11 percent of the variance in per capita employment can be attributed to changes in these technologies at a medium run horizon).

The impulse response functions graphed in Figures 10-12, tell a similar tale using a different metric. The results in the first of these figures show the responses of aggregate employment per capita and the unemployment rate to a 1 standard deviation technology shock. In all cases the unemployment rate falls significantly in response to the positive shock. The overall responses of aggregate employment, with the exception of that in mechanical/manufacturing, are positive and most significant for the cases of automotive and electrical technology. Figure 11 displays the analogous responses for hours per capita and employment per capita in the private non-farm sector. Again, we find that the response to a general technology shock (or a mechanical/manufacturing technology shock) is insignificantly different from zero. However, both measures of employment rise following automotive and electrical technology shocks. Finally, the graphs for manufacturing and transportation (Figure 12) show a positive relationship between employment opportunities and technology shocks. In fact, in almost all cases, employment in these sectors significantly increased for at least 5 years following the shock.

III.C. Sensitivity Results

We have assumed thus far that the relationship between technology, productivity, and employment is similar over the entire time period. The work of Cole and Ohanian (2004) raises serious questions about the validity of this assumption. In particular, if their argument that New Deal legislation led to major changes in the nature of the wage bargain and in the degree of competition is correct, then the assumed constancy of the relationship between technological change and productivity and employment is open to question.[28]

In addition to the parts of the regulation that Cole and Ohanian (2004) focus on, we know that portions of the legislation introduced during the depression were explicitly intended to limit the amount of new machinery and/or capital that could be purchased and installed in some sectors of the economy.[29] In a July 16, 1934 article in the New York Times entitled, "Durable Goods Industries," it was reported that of the 280 regulations in the National Recovery Administration (NRA), thirty-six of them "contained restrictions on the installation of new machinery and on increase in productive capacity".[30] In a more in-depth article that appeared in the Times a week earlier, it was noted that the limitations imposed in these thirty-six industry codes fell into four basic categories.[31] In one, which affected iron and steel, a direct prohibition was placed on the expansion of capacity. In nineteen others, capacity could be expanded only with authorization by the code authority.[32] Eighteen codes necessitated a recommendation by the code authority to expand capacity, while one (the motor vehicle storage and parking code) imposed restrictions

[28] As one might expect there is a vast literature on unemployment in the United States during the Great Depression. See, for example, Cole and Ohanian (2004), Margo (1993) and the references within these papers.

[29] See also Bernstein (1987) and Hawley (1964).

[30] The NRA was the agency empowered to carry out the provisions of the National Industrial Recovery Act.

[31] See the July 8, 1934 article in the New York Times, entitled Capital Industries Affected by Codes."

[32] Industries that required authorization to expand capacity included: lace manufacturing, cotton textiles, glass, ice, silk throwing, floor and wall clay tiles, transit, crushed stone, air transport, structural clay, cement, excelsior, pyrotechnics, refractories, rayon and silk dying, feldspar, American glassware, and carbon black

by agreement. Finally, the article noted that, on top of the explicit restrictions contained in thirty-six of the codes, there were other regulations passed in the first year of the NRA which indirectly discouraged the installation of new machinery by placing limitations on the number of hours machines could be run. Although there is no general consensus about the actual impact of this legislation on economic activity – the National Industrial Recovery Act was declared unconstitutional by the Supreme Court in 1935 – it is, of course, entirely possible that these restrictions did change the relationship between technical change and employment during the mid to late 1930s.[33] To find out if this was the case, we reran the regressions for private non-farm output per worker and private non-farm per capita employment with dummy variables included for the years 1934-1939. The results are reported in Table 7 alongside the original point estimates. While there are some differences, they are negligible, which leads us to conclude that our results are unaffected by the inclusion of the NRA years in our original data series. In light of this, it seems reasonable to argue that the sluggish recovery in employment after 1934 may be attributable, as Cole and Ohanian (2004) maintain, to very New Deal policies that were intended to preserve job opportunities.

IV. Conclusions

In this paper we attempt to determine the impact, if any, of technical change on employment for the period 1909-49. This is hardly a new issue – the idea that machines replace men dates back at least to early eighteenth century England if not earlier – but it has resisted satisfactory quantitative analysis because of the well-known difficulties in measuring technical change. The usual suspects are, for various reasons, not up to the task. Total factor or labor productivity provide at best indirect (and quite noisy) indicators of technical change while the traditional direct measures, such as patents, research and

[33] See "Some Legal Aspects of the National Industrial Recovery Act", in the *Harvard Law Review*, Vol. 47, No. 1. (Nov., 1933), pp. 85-125.

development expenditures, and innovation counts are dogged by a variety of problems. To resolve the difficulty, we estimate the relationship between technological innovation and employment for the period 1909-1949 using new indicators of technical change that are, on the whole, free from these problems. Our regression results suggest that technology shocks (and technical change) increased per capita employment/hours during the early part of the century with the largest impacts coming from changes in electrical/electronics and automotive technologies. For the most part, it appears that the economy's responses to technology shocks during this time are more consistent with the predictions of a neoclassical model than a new Keynesian one.

In addition to the issue of model selection, we would argue that our results shed light on an important policy debate –namely, can the slow economic recovery in the U.S. after 1933 be attributed, at least in part, to some of the more interventionist policies of the New Deal? Cole and Ohanian (2004) argue that, prior to 1934, the benchmark U.S. economy was neoclassical which meant that the economy should have bounced back quickly from the negative shocks that hit it in the early years of the decade. Its failure to do so indicates to them that some features of the economy changed fundamentally after 1933 – and they finger as the prime suspect NIRA legislation. Eggertson (2006), in contrast, observes that if the New Dealers were operating in a New Keynesian (instead of a neoclassical) world where there was severe deflation and the zero bound on nominal interest rates had been reached, then the very policies Cole and Ohanian (2004) believe stifled recovery could have actually fostered it. Resolution of the controversy depends at least in part on the nature of the benchmark economy prior to the introduction of NIRA and other New Deal legislation. Our results, based on the overall positive relationship between technological change and employment, would seem to come down on the side of Cole and Ohanian (2004).

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Figure 1: Articles on Technological Unemployment

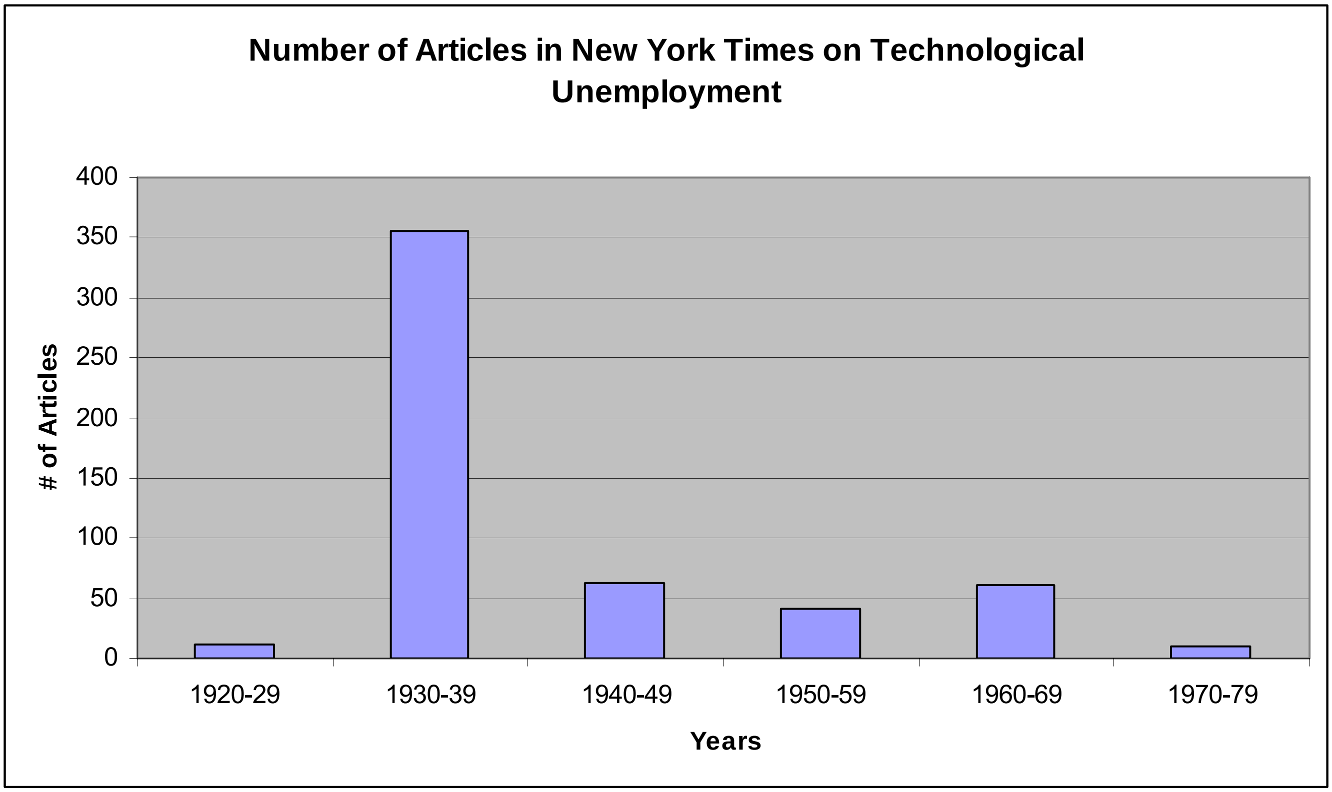

Figure 2: Graphs from New York Times Article, “March of the Machine Makes Idle Hands” by E. Clark (Feb 26, 1928. p. 129)

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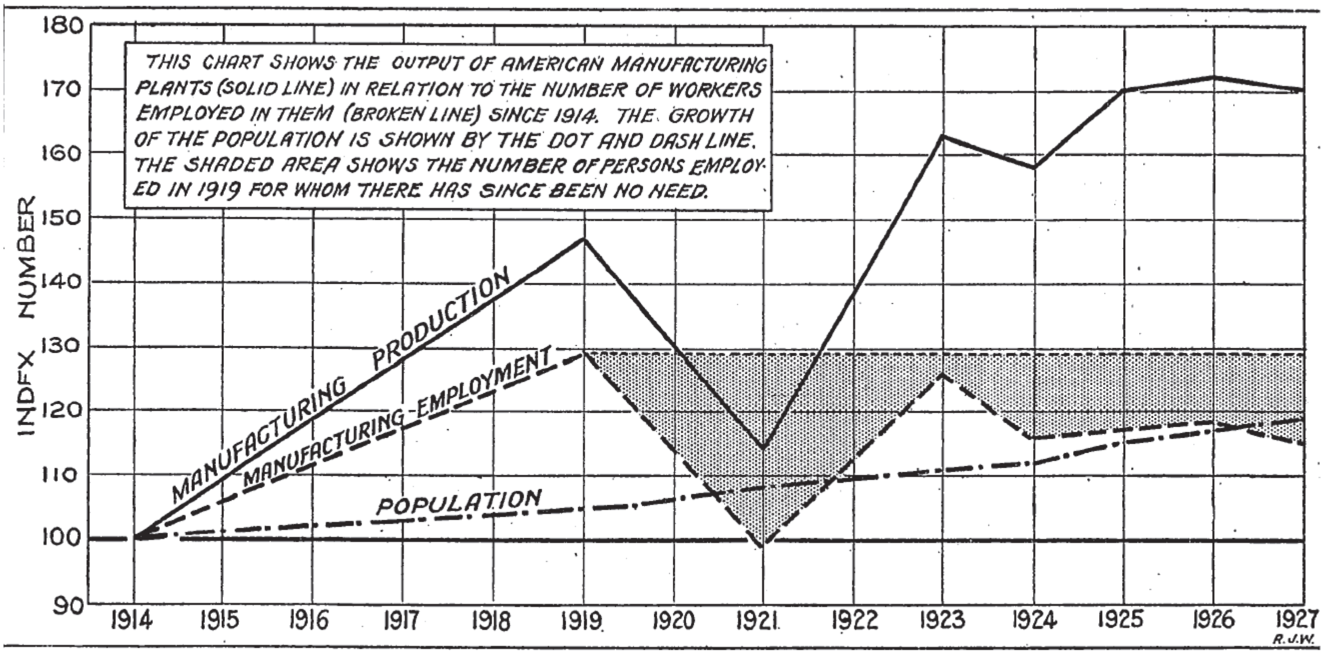

INDUSTRY CARRIES ON WITH FEWER HANDS

The Nation’s Factories Have Been Turning Out More Goods Than Ever While More Men Look for Work.

FARM EMPLOYMENT LESS WITH INCREASED OUTPUT

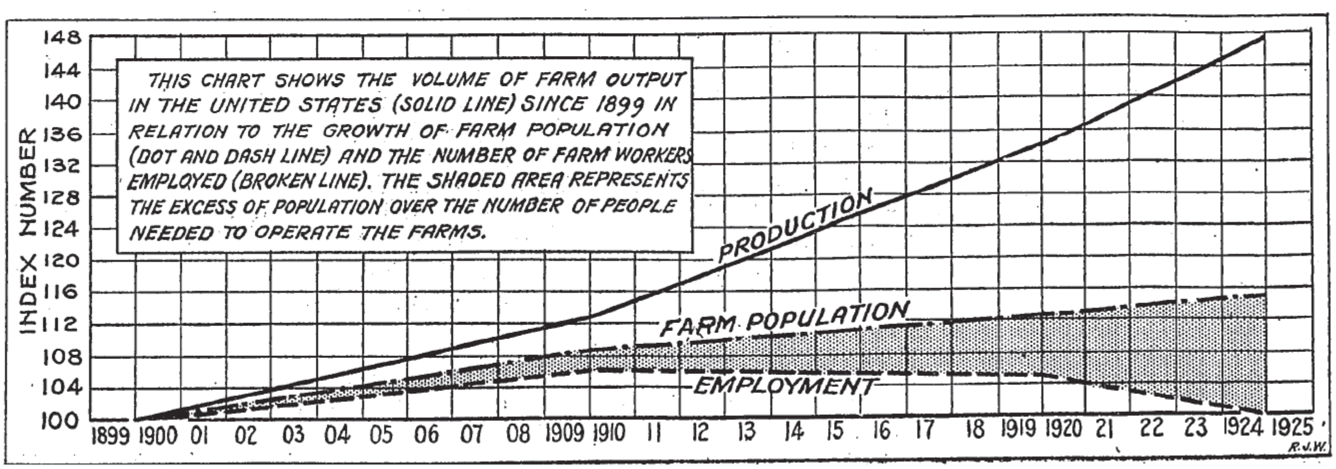

Figure 3: Employment and Unemployment

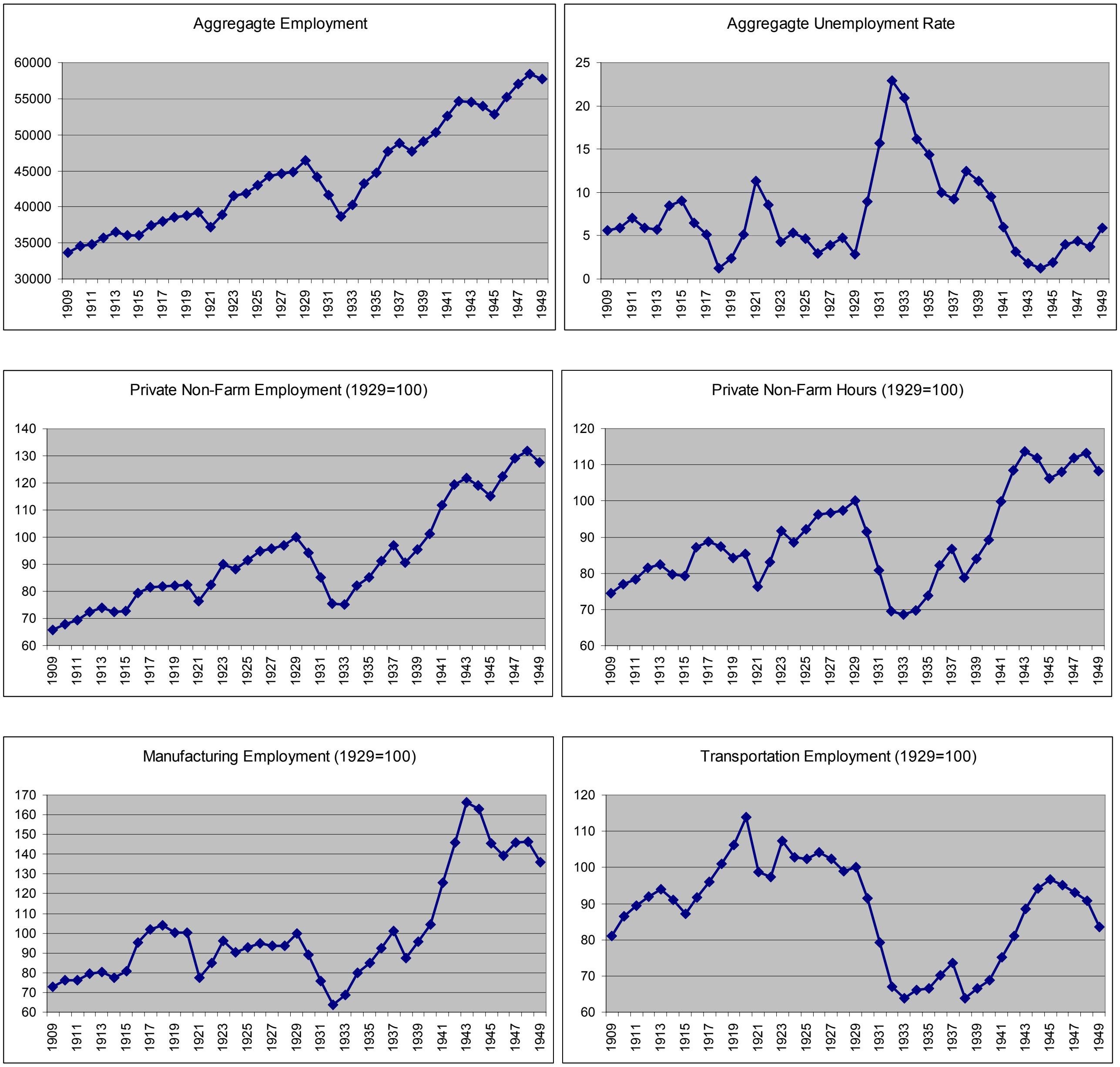

Figure 4: Productivity

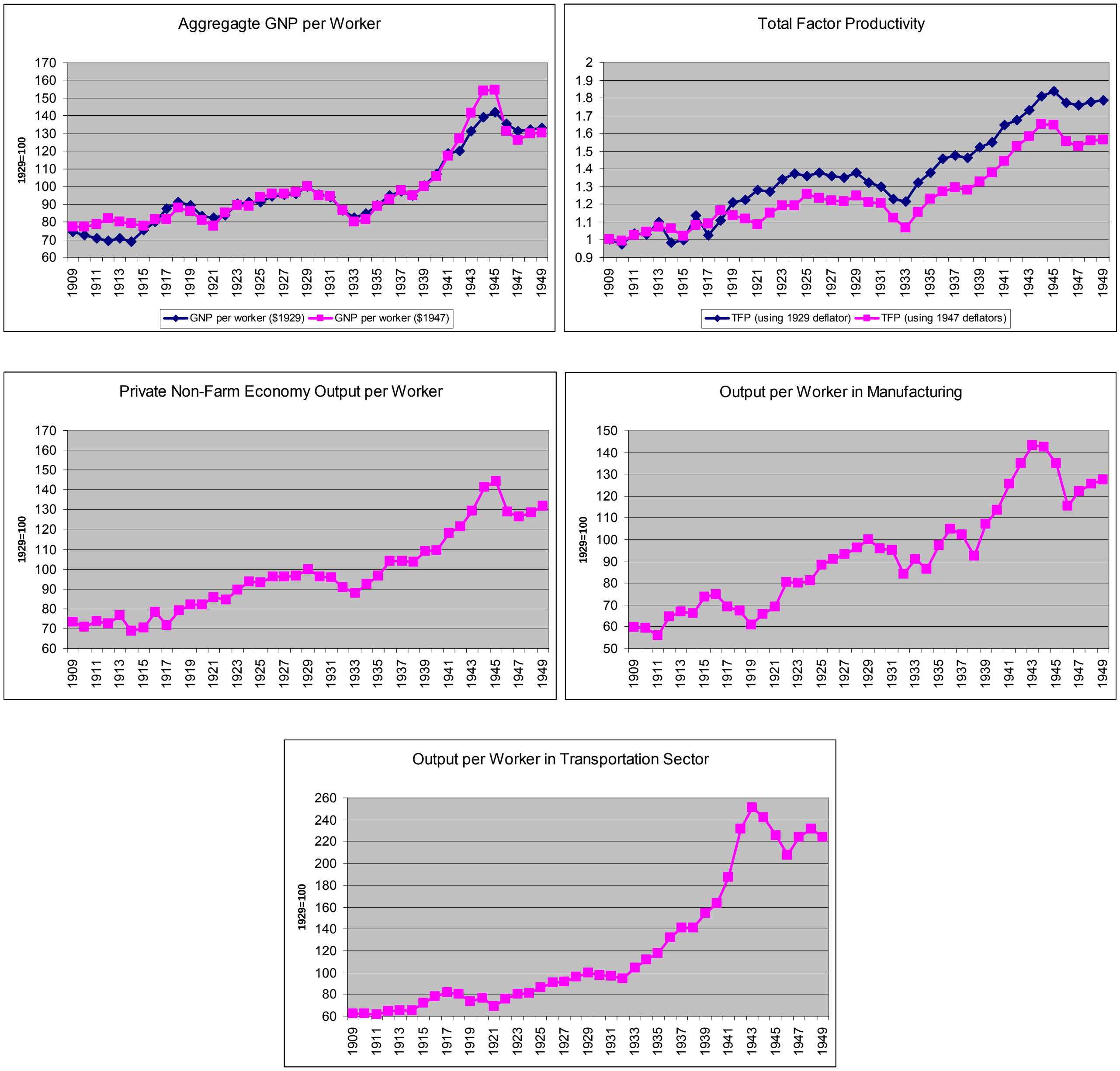

Figure 5: Sample Marc Record

Actual Record:

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43040050- a0bcbccpremunvduencipf19gy-gencatlg- a   43040050 - aDLCcCarPdDLC-00aTL260-
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c1939]- acover-title, 106 p.billus.c19 cm.- 0aAutomobilesxTransmission devices. [from old catalog]-2 -
aInternational correspondence schools, Scranton, Pa. [from old catalog]- bc-GenCollhTL260i.S77tCopy
1wPREM-□

Online Display of Marc Record for Title: Automatic transmissions, by C. Strouse

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LCCN Permalink: http://lccn.loc.gov/43040050
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Main Title: Automatic transmissions,
Published/Created: [Scranton, 1939]
Related Names: International correspondence schools, Scranton, Pa. [from old catalog]
Description: cover-title, 106 p. illus. 19 cm.
Subjects: Automobiles--Transmission devices. [from old catalog]
LC Classification: TL260 .S77

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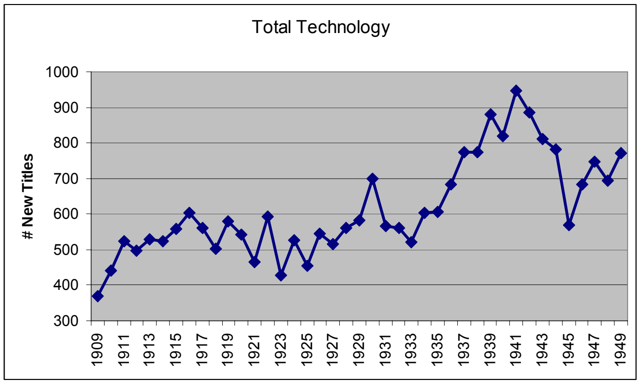
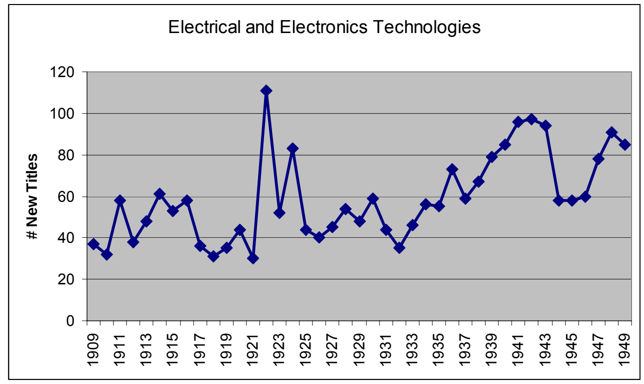
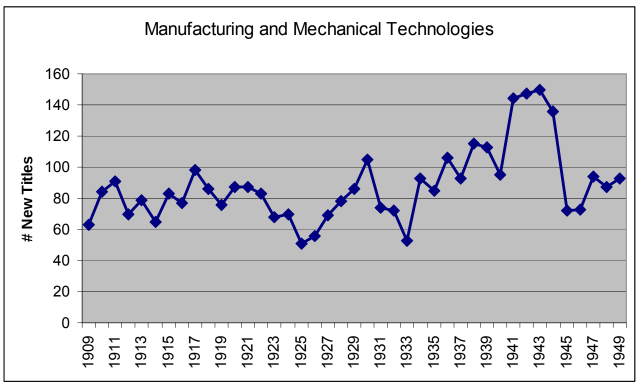
Copy 1
-- Request in: Jefferson or Adams Bldg General or Area Studies Reading Rms

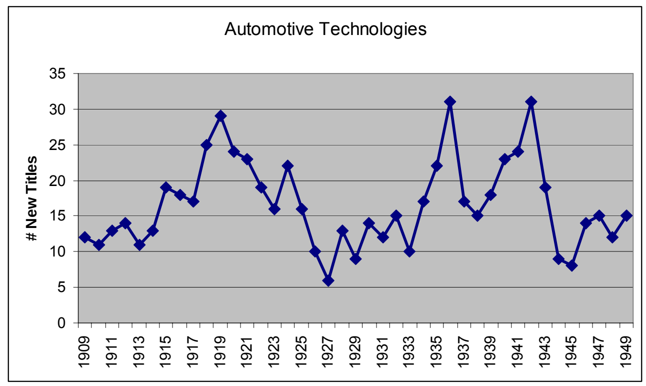
-- Status: Not Charged

Figure 6: The indicators









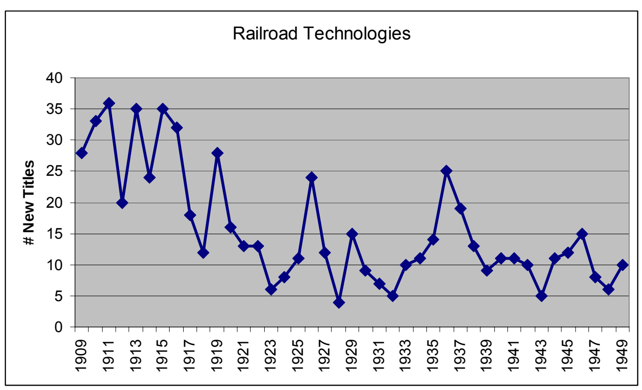
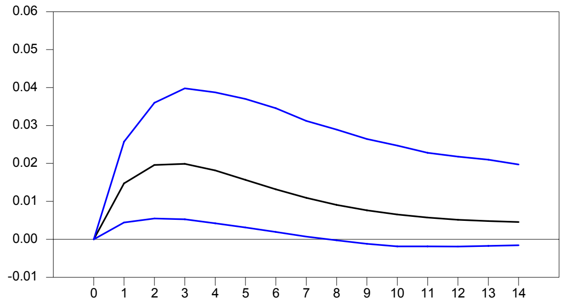


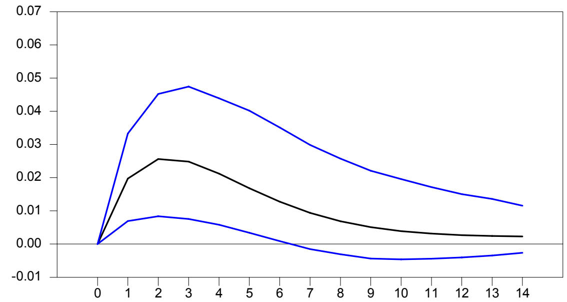
Figure 7: Responses of Labor Productivity in the Aggregate Economy

Total Technology Shock

GNP per worker ($1929)

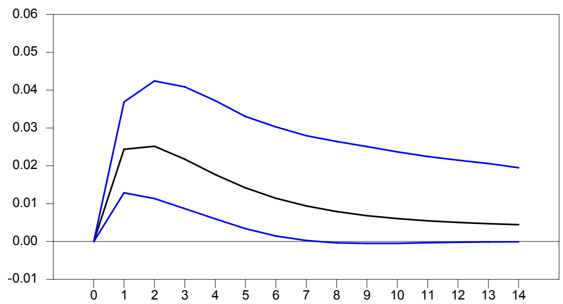


GNP per worker ($1947)

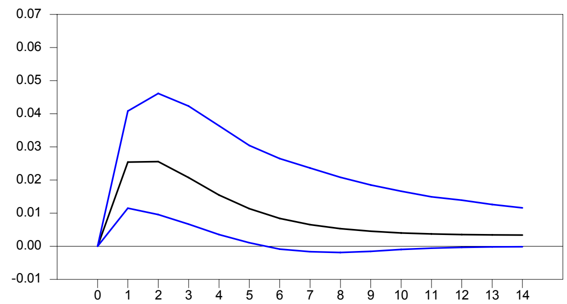


Electrical/Electronics Technology Shock

GNP per worker ($1929)

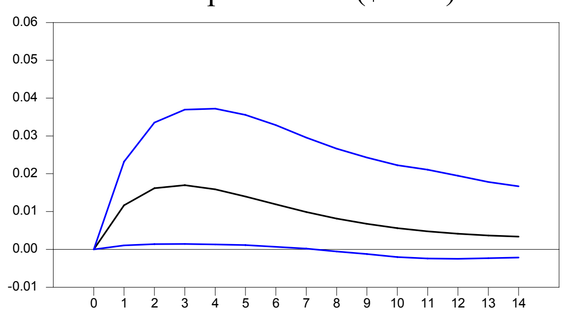


GNP per worker ($1947)

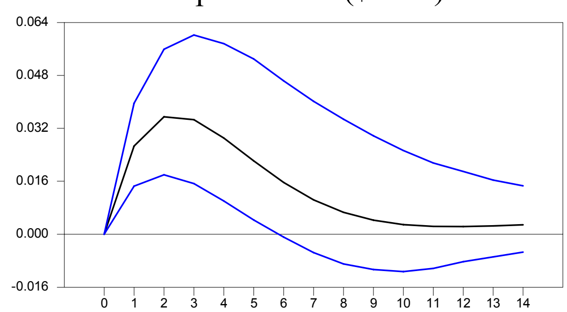


Mechanical/Manufacturing Technology Shock

GNP per worker ($1929)

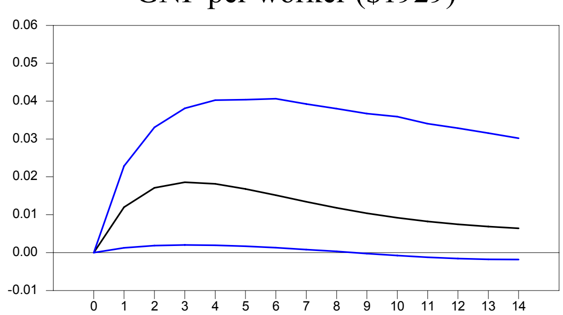


GNP per worker ($1947)



Automotive Technology Shock

GNP per worker ($1929)



GNP per worker ($1947)

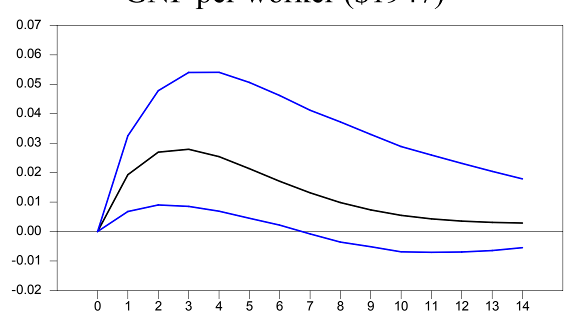
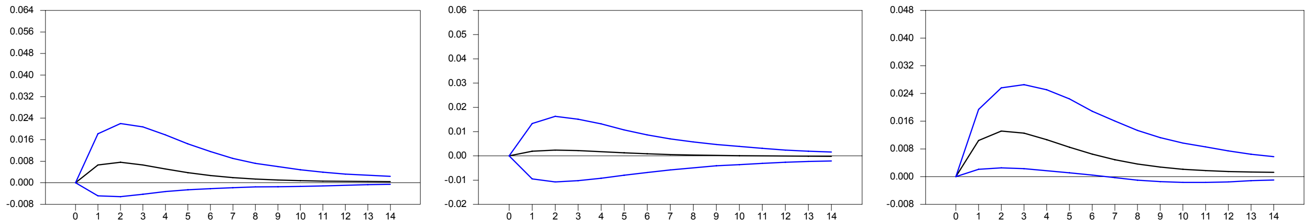


Figure 8. Responses of Productivity to a positive technology shock

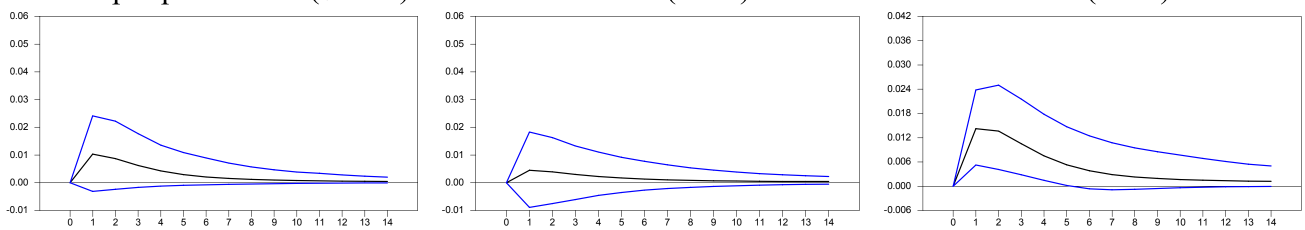
Total Technology Shock

Output per worker ($1929) | TFP (1929) | TFP (1947)



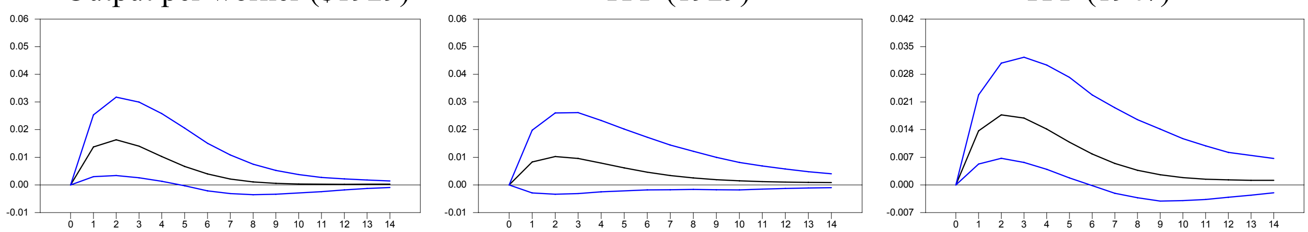
Electrical/Electronics Technology Shock

Output per worker ($1929) | TFP (1929) | TFP (1947)



Mechanical/Manufacturing Technology Shock

Output per worker ($1929) | TFP (1929) | TFP (1947)



Automotive Technology Shock

Output per worker ($1929) | TFP (1929) | TFP (1947)

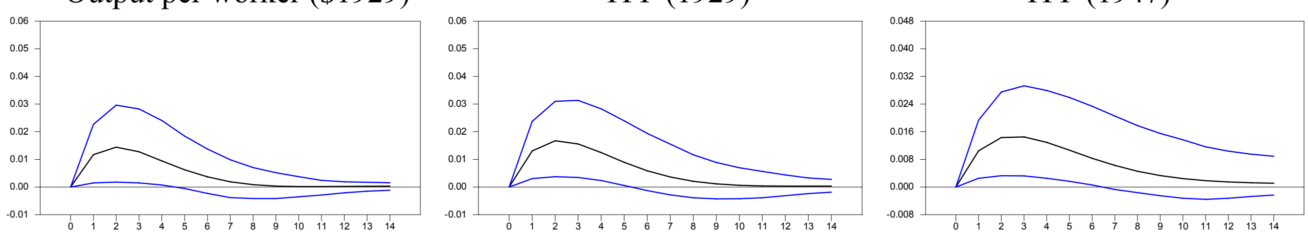


Figure 9. Responses of Output per worker in the Manufacturing and Transportation sectors

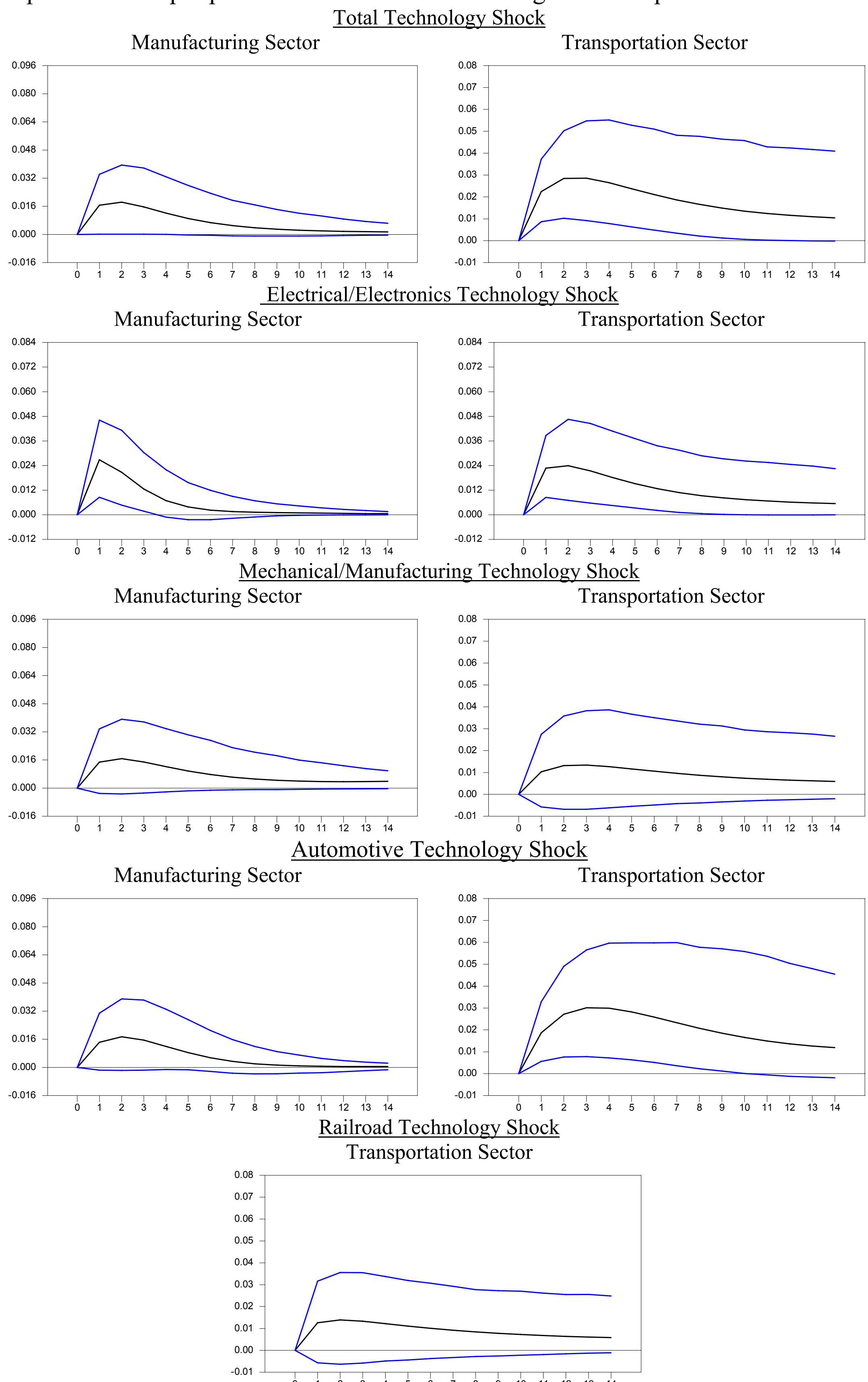
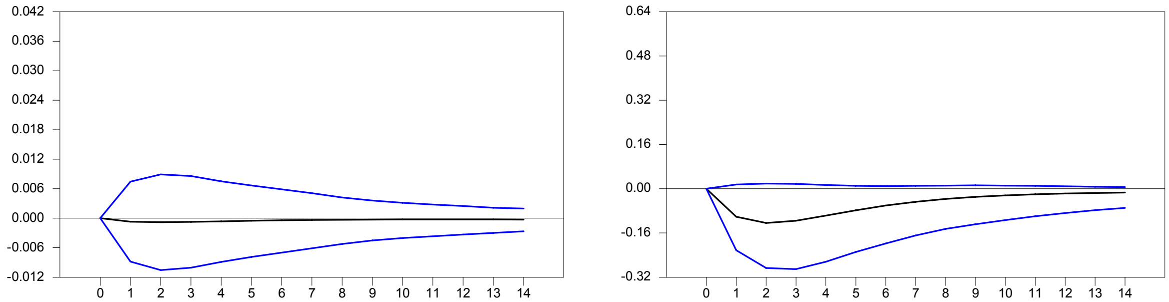


Figure 10. Responses of Employment per capita and the Unemployment rate for the total economy

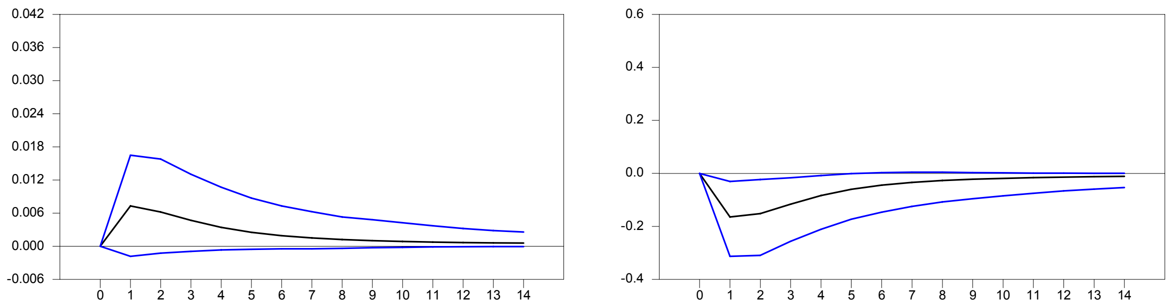
Total Technology Shock

Employment | Unemployment Rate



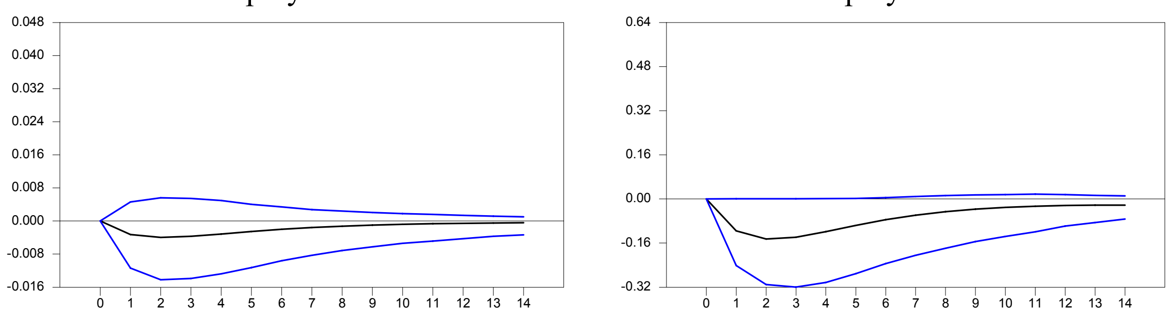
Electrical/Electronics Technology Shock

Employment | Unemployment Rate



Manufacturing/Mechanical Technology Shock

Employment | Unemployment Rate



Automotive Technology Shock

Employment | Unemployment Rate

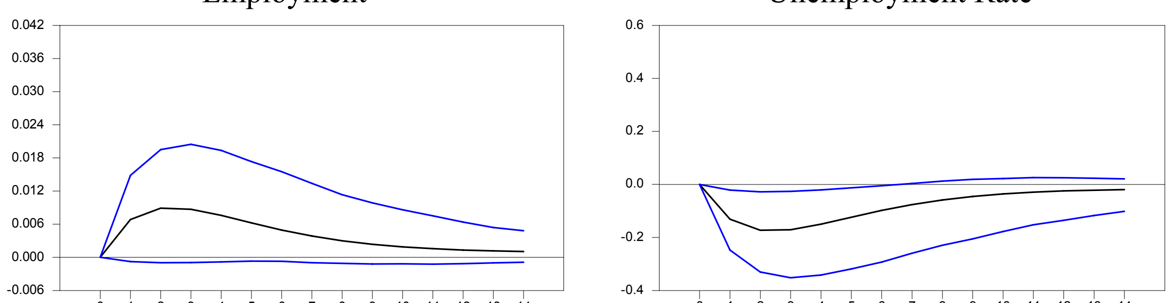
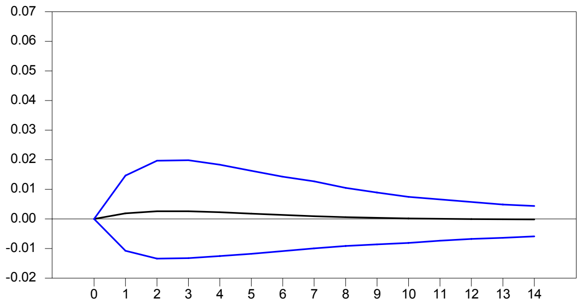


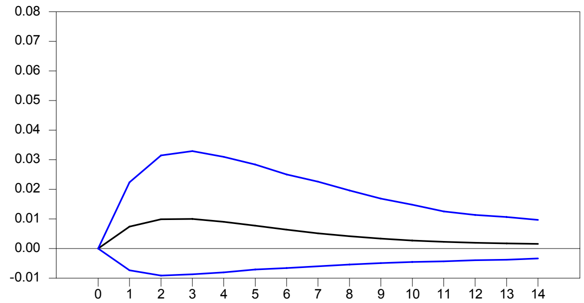
Figure 11. National Non-farm Per capita Employment and hours responses

Total Technology Shock

Employment

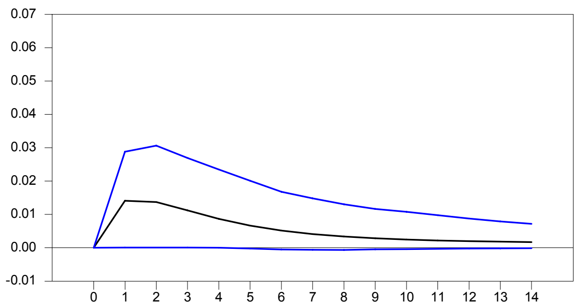


Hours

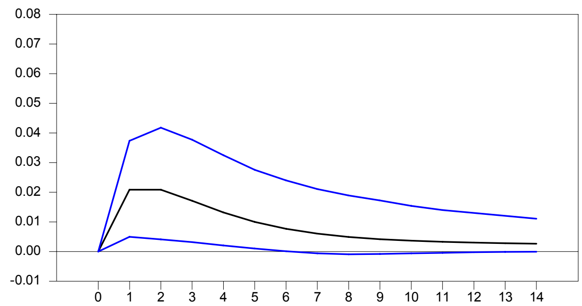


Electrical/Electronics Technology Shock

Employment

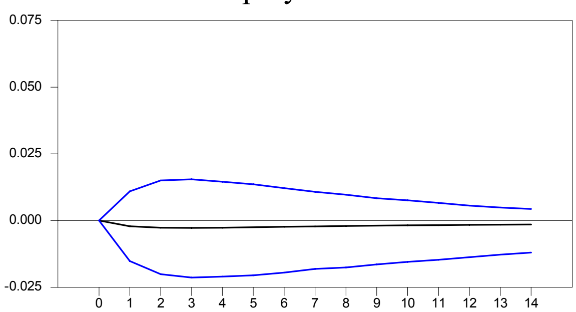


Hours

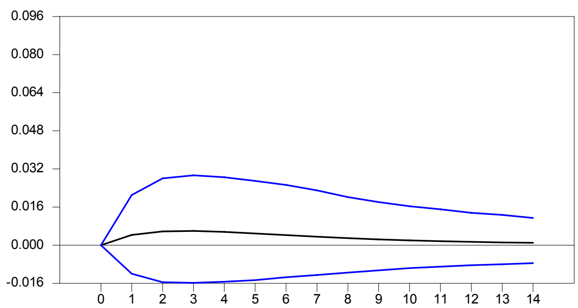


Manufacturing/Mechanical Technology Shock

Employment

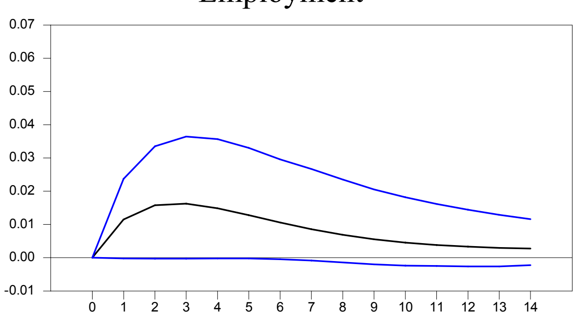


Hours



Automotive Technology Shock

Employment



Hours

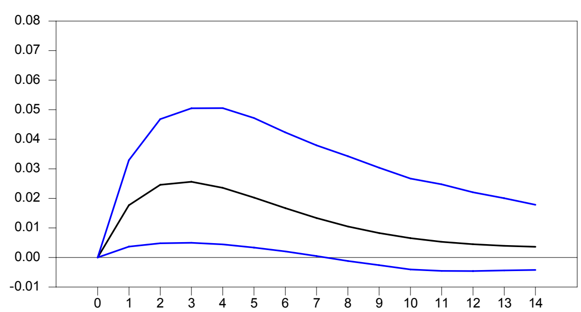


Figure 12. Responses of Per capita Employment in the Manufacturing and Transportation sectors

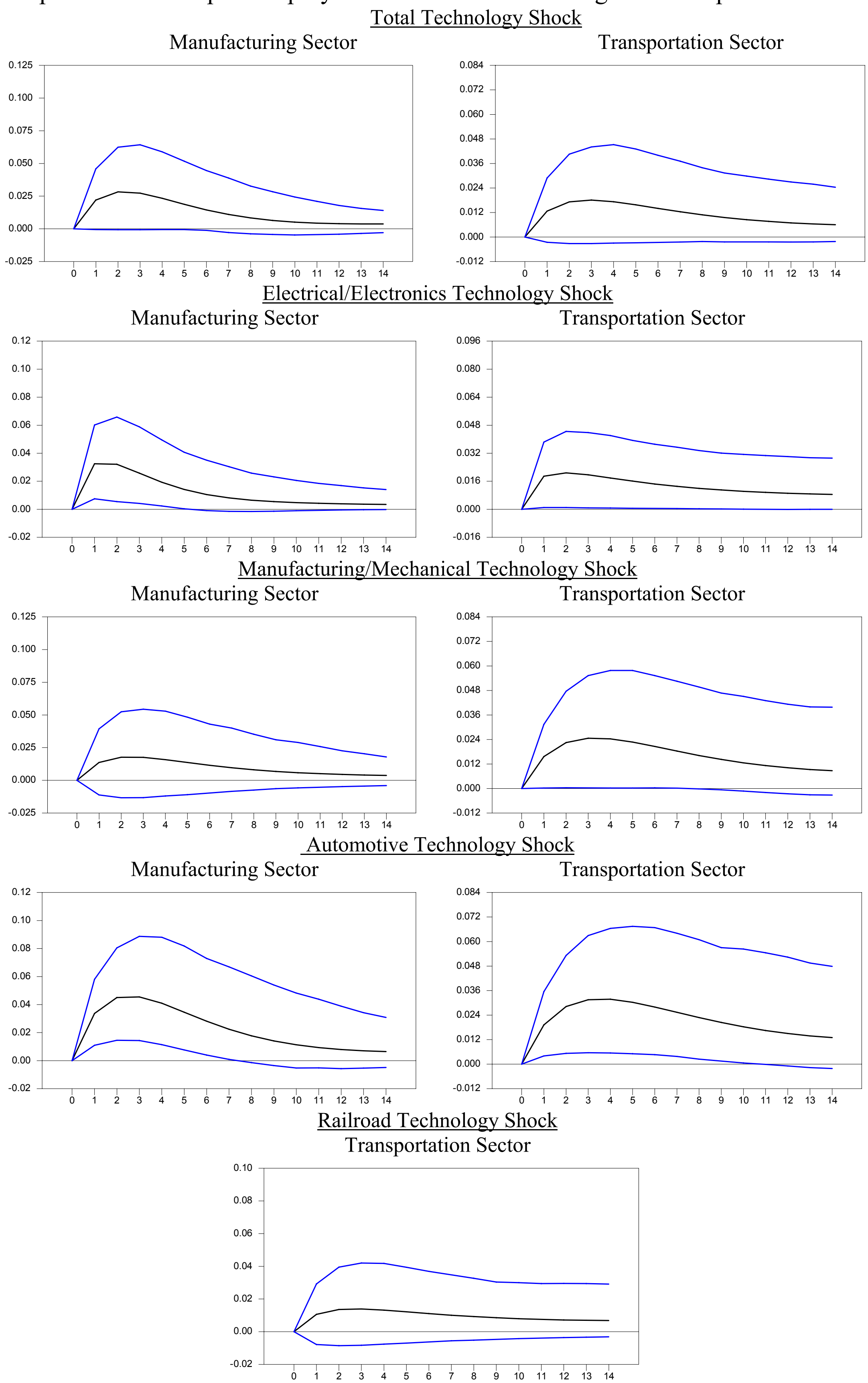


Table 1. Point Estimates and Standard Errors

Indicator	Aggregate Y/E		Aggregate Y/E 1947		Private Non-Farm Y/E		Private Non-Farm TFP 1929		Private Non-Farm TFP 1947		Manufacturing Y/E		Transportation Y/E	
	ρ	β	ρ	β	ρ	B	ρ	β	ρ	β	ρ	β	ρ	β
All Technology	0.8775	0.1215	0.8308	0.1644	0.6874	0.0541	0.7088	0.0154	0.8082	0.0855	0.6248	0.1324	0.8015	0.1924
	(0.0828)	(0.0498)	(0.0910)	(0.0596)	(0.1267)	(0.0556)	(0.1187)	(0.0523)	(0.0895)	(0.0391)	(0.1258)	(0.0788)	(0.0720)	(0.0702)
Manufacturing & Mechanical	0.8430	0.0596	0.7928	0.1359	0.6611	0.0705	0.7026	0.0397	0.7686	0.0710	0.6217	0.0718	0.8228	0.0564
	(0.0850)	(0.0320)	(0.0837)	(0.0344)	(0.1188)	(0.0327)	(0.1158)	(0.0315)	(0.0865)	(0.0233)	(0.1280)	(0.0502)	(0.0852)	(0.0513)
Electrical & Electronics	0.8912	0.0888	0.8244	0.0957	0.6662	0.0361	0.6926	0.0152	0.7796	0.0537	0.5551	0.1019	0.8238	0.0914
	(0.0749)	(0.0228)	(0.0877)	(0.0291)	(0.1235)	(0.0275)	(0.1198)	(0.0265)	(0.0874)	(0.0192)	(0.1250)	(0.0397)	(0.0700)	(0.0343)
Automotive	0.8643	0.0369	0.8808	0.0625	0.7213	0.0389	0.7057	0.0408	0.8342	0.0306	0.7015	0.0461	0.8648	0.0585
	(0.0847)	(0.0191)	(0.0939)	(0.0230)	(0.1238)	(0.0203)	(0.1107)	(0.0181)	(0.0899)	(0.0146)	(0.1290)	(0.0302)	(0.0690)	(0.0249)
Railroad	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.8398	0.0278
	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	(0.0770)	(0.0226)

* For all cases the results correspond to the regression $\ln(\text{productivity}_t)=\alpha+\gamma t+\beta\ln(\text{Tech}_{t-1})+\rho\ln(\text{productivity}_{t-1})+\varepsilon_t$, where productivity is either Y/E or TFP

Table 2. Granger Causality Tests (P-values)

Do the technology indicators Granger Cause labour productivity or TFP?

Indicator	Aggregate Y/E ($1929)	Aggregate Y/E ($1947)	Private Non-Farm Y/E ($1929)	TFP private non-farm (1929)	TFP private non-farm (1947)	Manufacturing Y/E ($1929)	Transportation Y/E ($1929)
All Technology	0.020	0.009	0.337	0.771	0.035	0.102	0.010
Manufacturing & Mechanical	0.071	0.000	0.038	0.216	0.004	0.161	0.279
Electrical & Electronics	0.000	0.002	0.197	0.570	0.008	0.015	0.011
Automotive	0.061	0.010	0.064	0.030	0.043	0.136	0.025
Railroad	n/a	n/a	n/a	n/a	n/a	n/a	0.227

Do the productivity variables Granger Cause the technology indicators?

Indicator	Aggregate Y/E ($1929)	Aggregate Y/E ($1947)	Private Non-Farm Y/E ($1929)	TFP private non-farm (1929)	TFP private non-farm (1947)	Manufacturing Y/E ($1929)	Transportation Y/E ($1929)
All Technology	0.107	0.085	0.140	0.214	0.415	0.661	0.646
Manufacturing & Mechanical	0.224	0.121	0.069	0.245	0.336	0.947	0.249
Electrical & Electronics	0.092	0.095	0.450	0.737	0.525	0.516	0.873
Automotive	0.302	0.047	0.018	0.061	0.141	0.048	0.436
Railroad	n/a	n/a	n/a	n/a	n/a	n/a	0.171

Table 3. Variance Decompostions

Indicator	Horizon	GNP per employee ($1929)	GNP per employee ($1947)	Private Non-Farm Output per Employee	Private Non-Farm TFP (1929)	Private Non-Farm TFP (1947)	Manufacturing Output per employee ($1929)	Transportation Output per employee ($1929)
All Technology	3 years	11.19	14.31	2.43	0.22	10.24	7.41	12.40
	6 years	19.08	23.50	3.79	0.38	17.75	11.17	19.01
	9 years	20.88	24.76	3.91	0.40	19.40	11.48	20.69
Manufacturing & Mechanical	3 years	7.03	26.95	11.08	4.16	18.70	6.03	2.75
	6 years	13.12	41.08	16.78	7.42	31.12	9.66	4.64
	9 years	14.77	42.14	16.90	7.87	33.06	10.11	5.21
Electrical & Electronics	3 years	21.59	15.74	4.51	0.89	13.06	12.91	9.32
	6 years	26.25	19.10	5.39	1.11	16.20	14.18	11.61
	9 years	26.94	19.39	5.44	1.13	16.59	14.19	12.06
Railroad	3 years	n/a	n/a	n/a	n/a	n/a	n/a	3.77
	6 years	n/a	n/a	n/a	n/a	n/a	n/a	5.58
	9 years	n/a	n/a	n/a	n/a	n/a	n/a	6.09
Automotive	3 years	8.58	15.29	8.54	11.31	9.27	5.91	10.93
	6 years	17.80	28.27	13.76	19.52	18.49	9.87	21.84
	9 years	20.90	30.54	13.88	19.97	20.81	10.09	25.60

Table 4. Point Estimates and Standard Errors

Indicator	Aggregate Employment		Aggregate Unemployment Rate		Private Non-Farm Employment		Private Non-Farm Hours		Manufacturing Employment		Transportation Employment	
	ρ	β	ρ	β	ρ	β	ρ	β	P	β	ρ	β
All Technology	0.7375	-0.0057	0.7573	-0.8188	0.7897	0.0156	0.8055	0.0621	0.7606	0.1869	0.9102	0.1082
	(0.1242)	(0.0398)	(0.1115)	(0.5488)	(0.1001)	(0.0599)	(0.0941)	(0.0723)	(0.0999)	(0.1118)	(0.0722)	(0.0777)
Manufacturing & Mechanical	0.7569	-0.0166	0.7286	-0.5694	0.7976	-0.0104	0.8079	0.0213	0.7631	0.0700	0.9004	0.0804
	(0.1225)	(0.0246)	(0.1106)	(0.3410)	(0.1004)	(0.0376)	(0.0952)	(0.0458)	(0.1061)	(0.0744)	(0.0700)	(0.0465)
Electrical & Electronics	0.6786	0.0266	0.7723	-0.5810	0.7585	0.0522	0.7820	0.0795	0.7689	0.1220	0.8917	0.0658
	(0.1209)	(0.0196)	(0.1085)	(0.2709)	(0.0971)	(0.0294)	(0.0893)	(0.0348)	(0.0956)	(0.0542)	(0.0697)	(0.0376)
Automotive	0.7064	0.0211	0.7622	-0.4096	0.7896	0.0360	0.8297	0.0559	0.7451	0.1039	0.9112	0.0604
	(0.1149)	(0.0138)	(0.1087)	(0.2003)	(0.0955)	(0.0214)	(0.0891)	(0.0256)	(0.0948)	(0.0397)	(0.0689)	(0.0274)
Railroad	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.8983	0.0239
	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	(0.0721)	(0.0233)

* For all cases the results correspond to the regression $\ln(Y_t)=\alpha+\gamma t+\beta \ln(Tech_{t-1})+\rho \ln(Y_{t-1})+\varepsilon_t$, where Y= per capita employment, the unemployment rate, or per capita hours

Table 5. Granger-Causality Tests (P-values)

Do the technology indicators Granger Cause employment, unemployment or hours?

Indicator	Aggregate Employment	Aggregate Unemployment Rate	Private Non-Farm Employment	Private non-farm Hours	Manufacturing Employment	Transportation Employment
All Technology	0.886	0.145	0.796	0.396	0.103	0.172
Manufacturing & Mechanical	0.504	0.104	0.783	0.644	0.353	0.092
Electrical & Electronics	0.184	0.039	0.085	0.028	0.031	0.089
Automotive	0.135	0.048	0.101	0.036	0.013	0.034
Railroad	n/a	n/a	n/a	n/a	n/a	0.313

Do the productivity variables Granger Cause the technology indicators?

Indicator	Aggregate Employment	Aggregate Unemployment Rate	Private Non-Farm Employment	Private non-farm Hours	Manufacturing Employment	Transportation Employment
All Technology	0.513	0.262	0.322	0.228	0.229	0.043
Manufacturing & Mechanical	0.232	0.370	0.884	0.647	0.923	0.123
Electrical & Electronics	0.815	0.147	0.567	0.332	0.256	0.485
Automotive	0.388	0.235	0.198	0.114	0.492	0.187
Railroad	n/a	n/a	n/a	n/a	n/a	0.225

Table 6. Variance Decompositions

Indicator	Horizon	Aggregate Employment	Aggregate Unemployment Rate	Private Non-Farm Employment	Private Non-Farm Hours	Manufacturing Employment	Transportation Employment
All Technology	3 years	0.06	5.49	0.16	1.63	6.02	3.63
	6 years	0.10	9.35	0.30	3.06	10.47	6.51
	9 years	0.11	9.94	0.34	3.43	11.21	7.42
Manufacturing & Mechanical	3 years	1.30	7.30	0.21	0.58	2.37	5.83
	6 years	2.32	12.82	0.43	1.16	4.42	11.33
	9 years	2.51	13.66	0.51	1.35	4.95	13.22
Electrical & Electronics	3 years	4.32	10.26	6.22	8.71	8.96	6.23
	6 years	5.17	12.54	7.78	10.84	11.10	8.46
	9 years	5.25	12.73	7.98	11.09	11.31	9.04
Railroad	3 years	n/a	n/a	n/a	n/a	n/a	2.31
	6 years	n/a	n/a	n/a	n/a	n/a	3.70
	9 years	n/a	n/a	n/a	n/a	n/a	4.12
Automotive	3 years	6.22	10.50	6.65	10.43	16.46	9.95
	6 years	11.87	19.82	13.35	20.30	29.56	20.59
	9 years	12.86	21.31	14.93	22.49	31.98	24.55

Table 7: Sensitivity Analysis

Indicator	Private Non-Farm Employment				Private Non-Farm output per worker			
	without dummies		with dummies		without dummies		with dummies	
	β	ρ	β	ρ	β	ρ	β	P
All Technology	0.0156	0.7897	0.0399	0.8961	0.0545	0.6898	0.0675	0.6954
	(0.0502)	(0.0635)	(0.0588)	(0.1589)	(0.0677)	(0.1255)	(0.0836)	(0.2183)
Electrical & Electronics	0.0522	0.7585	0.0480	0.8583	0.0361	0.6662	0.0374	0.6526
	(0.0214)	(0.0587)	(0.0197)	(0.1452)	(0.0290)	(0.1041)	(0.0325)	(0.1777)
Mechanical & Manufacturing	-0.0105	0.7976	-0.0104	0.9048	0.0705	0.6611	0.0814	0.6612
	(0.0277)	(0.0657)	(0.0317)	(0.1679)	(0.0391)	(0.1093)	(0.0428)	(0.1687)
Automotive	0.0360	0.7896	0.0386	0.8964	0.0389	0.7213	0.0479	0.7501
	(0.0185)	(0.0747)	(0.0218)	(0.1691)	(0.0163)	(0.1190)	(0.0218)	(0.2089)

*For all cases the results correspond to the regression $\ln(Z_t)=\alpha+\gamma t+\beta\ln(Tech_{t-1})+\rho\ln(Z_{t-1})+\varepsilon_t$, where Z= per capita employment, or output per worker

Appendix A. Library of Congress Classification Overview

Subclass T Technology (General)

Subclass TA Engineering (General). Civil engineering

Subclass TC Hydraulic engineering. Ocean engineering

Subclass TD Environmental technology. Sanitary engineering

Subclass TE Highway engineering. Roads and pavements

Subclass TF Railroad engineering and operation

Subclass TG Bridge engineering

Subclass TH Building construction

Subclass TJ Mechanical engineering and machinery

Subclass TK Electrical engineering. Electronics. Nuclear engineering

Subclass TL Motor vehicles. Aeronautics. Astronautics

Subclass TN Mining engineering. Metallurgy

Subclass TP Chemical technology

Subclass TR Photography

Subclass TS Manufactures

Subclass TT Handicrafts. Arts and crafts

Subclass TX Home economics