The Media is the Measure:

Technical change and employment, 1909-49

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Abstract: New indicators, based on technology titles, are used to measure the impact of innovative activity on the U.S. labor market between 1909 and 1949. We find positive technology shocks raised productivity, employment, vacancies and labor turnover and lowered unemployment. Moreover, innovations in automotive and electrical had a greater positive impact on employment than those in mechanical. The overall results, compatible with the predictions of the real business cycle model, raise questions about the anemic recovery in employment after 1934 since the strong upsurge in technical change failed to be accompanied by an equally vigorous expansion in jobs.

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

JEL: E2, E3, N1, O3

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Introduction:

The impact of technical change on hours and employment at business cycle frequencies is a subject of intense debate among modern macroeconomists. In the standard New Keynesian models, prices are assumed to be sticky and monetary policy non-accommodating so that technology shocks cause employment (hours worked) to fall in the short run.[1] In the traditional neoclassical business cycle model, on the other hand, rigidities are absent and technology shocks have an immediate positive effect on employment. It follows then that empirical evidence on the short-run relationship between technical change and employment should aid in model selection, shed light on the underlying economy, and thus contribute to resolution of the debate. In an attempt to advance the literature on this subject, we use in a series of vector autoregeressions for the period 1909-1949 new direct measures of technical change to pinpoint the impact of technology shocks on labor market variables.

Our choice of time period is not accidental. While most, with the exception of Francis and Ramey (2004), focus on the post WWII years, there are compelling reasons to look at the earlier decades of the last century. First, the U.S. economy was subject to more frequent, longer, and deeper business cycles (including, of course, the worst on record) during the first half of the 20th century than during any subsequent period. Second, the 1920s and, especially, the 1930s were times of rapid technical progress where significant advances were registered across a large number of industries and types of innovations, including two major general purpose technologies (GPT) - electricity and automobiles - and one near GPT – machinery. Third, high rates of unemployment dogged the U.S. economy throughout the 1930s, even after 1934 as the economy started to recover and technical change hit record highs.[2] Roosevelt along with many in his administration seemed to believe that these technical advances were major contributors to the paucity of new employment opportunities.[3] Others, instead, contend that it was the very policies introduced by the administration to abet recovery that held back job growth.[4] As we explain below, our

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[1] Other types of rigidities have also been used to generate this outcome.

[2]. See e.g., Margo (1993), Bernanke (2000), and Temin (2000).

[3] See Bix (2000).

[4] See Cole and Ohanian (2004).

new indicators highlight the source of Roosevelt's concern and help us pinpoint technology's role in the recovery.

These new measures, based on information in the Library of Congress' (LOC) MARC records database and the publication lists in R.R. Bowker Company's *Publisher's Weekly* (PW)[5], embody the full range of features considered desirable in such indicators – they are objective, consistent over time, and capture innovations at the moment of their commercialization.[6] They suffer from few of the shortcomings associated with traditional direct measures, and, unlike indirect ones such as those based on cleansed Solow residuals[7] or long run restrictions[8], they focus unambiguously on new technologies. These new indicators have an additional attractive feature. Since they allow us to break down overall technical advances into various sub-groups such as electrical, automotive, and mechanical (our GPT and near GPT technologies), we can thus use them to determine if the employment effect of technological change varies with the type of technology shock.

To summarize our findings briefly, we observe, first, in keeping with Francis and Ramey (2004), a positive relationship between aggregate technology shocks and employment in the short and medium runs at both annual and monthly frequencies.[9] In short, even

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[5] The LOC data are available for the entire 40 -year period, the PW numbers for the years 1920-49.

[6] For the post-war period, macroeconomists have attempted to uncover the response of labor to technology shocks using direct measures of technical change such as patent applications and research and development expenditures (Shea 1998), and indirect ones such as purified Solow residuals (Basu, Fernald, and Kimball 2006; Christiano, Eichenbaum, and Vigfusson 2004), and long run identifying restrictions (Gali 1999; Francis and Ramey 2005; Christiano, Eichenbaum, and Vigfusson 2003; Fisher 2006) in vector autoregressions.

[7] As is well known, the residuals can be biased, among other things, by changes in regulation, utilization rates, and levels of aggregation.

[8] Long run restrictions can be affected by other shocks in the presence of endogenous growth and/or changes in rates of capital taxation.

[9] Although we focus on the relationship between technical change, productivity, and employment, it is likely that technical change during this period also impacted wages and overall wage inequality. Margo (1993) and Goldin (2000) both hint at this possibility while Barlevy and Tsiddon (2006) find evidence that it may have reduced inequality, at least in the upper wage range, during the 1930s.

if the economy was saddled with frictions, imperfections, and/or price and wage rigidities, the evidence suggests that they were insufficient to offset the positive impact of technical change on employment. Second, we find that the book-based measures of technology explain a significant portion of the variance in employment, especially at monthly frequencies. Third, consistent with the predictions of a standard search model, while innovations during this period created new jobs, destroyed old ones, and changed skills requirements, the bottom line is that they boosted job opportunities – vacancies rose and the unemployment rate fell.[10] Finally, our data suggest that technical change increased turbulence in the manufacturing sector –the median layoff rate dropped while the gross accession rate, total separations, quits, and discharges all increased.[11]

Furthermore, when disaggregated by type of technology, automotive and electrical innovations (the GPTs) had a greater positive impact on employment than those in mechanical (the near GPT). How do we explain these different outcomes? Evidence from the industrial organization literature suggests that while both product and process based technological change can increase productivity at the firm and industry level, their impact on labor demand often differs. [12] New products create new markets and usually boost employment, new processes frequently save labor and thus cause employment to fall.[13] Although all of the groups contained substantial process advances, electrical and automotive technologies also had strong product components that may have fostered job growth. [14,15] In this respect, it is quite possible that the Roosevelt administration's preoccupation

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[10] This is consistent with the effect of the standard search model.

[11] For work examining the empirical effects of technology shocks on job flows and turnover in the post-WWII period see Justiniano and Michelacci (2011), Michelacci and Lopez-Salido (2007) and Davis and Haltiwanger (1999).

[12] See, for example, Spiezia and Vivarelli (2002); Harrison et al. (2008).

[13] Shea (1998), one of the first to make the product-process distinction in a macro analysis, finds that advances in process technologies is more likely to raise productivity, lower prices, and boost employment than product based innovations. Shea maintains that this contrast with the findings of micro level studies is linked to the inability of his price data to reflect quality changes in products.

[14] The idea that the employment effects of GPTs and near GPTs may be affected by the relative amount of process and products innovations associated with them is advanced by Lipsey et al

with the labor displacing effects of new technologies was largely a consequence of its focus on innovations in manufacturing.[16] Had it been able to take a broader perspective that encompassed the rapid growth of new products linked to automotive and electrical advances, the administration may have been more sanguine about the employment impact of these new technologies. It may even have embraced the idea that the great wave of gadgets that swept over the U.S. from the mid-1930s actually prevented a bad situation from becoming a good deal worse.

We proceed as follows. In the next section, we present the data we use in the regressions, describe our indicators, and review their intuitive appeal. In section three, we report and analyze our results. In section four, we summarize our findings and identify areas for future research.

2. The Data And The New Indicators

2.1. Annual Employment and Productivity Statistics 1909-49

Since there are no official series produced for the early part of our sample, we are compelled to use standard ones created by others. 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 on aggregate employment and the aggregate unemployment rate come from the *Historical Statistics of the United States Millennial Edition* (Table Ba 470-477) which are, in turn, taken from Weir (1992) whose numbers represent a thorough reconsideration and, where necessary, revision of those originally developed by Lebergott (1964).. GNP per person (1947 constant dollars) comes from the Economic Almanac of the National Conference Board while Solow (1957) and Goldsmith (1956) are

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(2005) and Stoszak (2007). Although electricity is often viewed as the quintessential process technology, in fact, it was heavily product oriented at least during this period with the spread of residential electrification and the adoption new household appliances.

[15] Data limitations force us to restrict our sub-group analyses to annual frequencies.

[16] A main source of information for Roosevelt about the impact of technical change on employment came from industry based studies, almost exclusively in manufacturing, conducted by the National Research Project. However, the economists engaged in the project were careful to note that it was unwise and unwarranted to draw macroeconomic conclusions from a restricted set of microeconomic data.

the sources for data required to compute TFP for the private non-farm economy. 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.

A few features of the data are worth highlighting. First, as is well known, aggregate unemployment jumped sharply in the 1930s. Moreover, as the numbers suggest, the rise in unemployment and the drop in employment opportunities encompassed many sectors including such major ones as 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.

2.2. Monthly Productivity measures and Labor Market variables

As we are unable, because of data limitations, to calculate total factor productivity at monthly frequencies, we utilize instead two labor productivity measures. Specifically, at the aggregate level we follow Carlino et al. (2001) and Horvath and Verbrugge (1996) and define productivity in a given month to be the Federal Reserve Board's index of industrial production divided by the number of employees working in nonagricultural establishments (available from the NBER). For manufacturing, we use the ratio of industrial production to employment in the sector.

To explore the relationship between more detailed labor market variables and technical change at a monthly frequency, we make use of 10 series taken from the NBER's Macrohistory Database. The series spanning January 1929 – December 1949 include Employees in Nonagricultural Establishments and Total Production Worker Employment in Manufacturing produced by the Bureau of Labor Statistics (BLS) and the unemployment rate as reported by the National Conference Board. For the period June 1920 to December 1949, we have data on the index of total production worker man-hours in manufacturing drawn from the National Industrial Conference board, the NBER and the Bureau of the Census, vacancies estimated from Help-Wanted Ads in newspapers produced by W.A. Berridge of Metropolitan Life Insurance Company, and, finally, labor turnover in manufacturing – the quit rate, layoff rate, discharge rate, total separation rate, and gross accession rate –collected by the BLS.[17]

2.3. Indicators of Technological change

As argued in the introduction, an ideal indicator of technical change should be consistent over time, objective, quantifiable, and able to capture an innovation at the moment of its commercialization. All the usual suspects fail to meet one or more of these requirements. Research and development expenditures measure inputs into the inventive process not outputs of commercially viable innovations.[18] While patent applications and/or grants do represent potentially valuable new additions to economic knowledge[19], the long and uncertain lags associated with their commercial adoption make them at best imperfect indicators for our purpose. They are, in addition, compromised for the 1930s because a surge in judicial hostility to corporate patents led to a decline in corporate patent applications. (Schmookler (1961)) Although innovation counts resolve some of these problems, they are difficult to quantify and are notoriously subjective.[20] 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 may be affected by factors other than technical change (e.g., changes in regulations, learning by doing) and thus fail to provide a foolproof measure of commercialized technology.

The indicators presented here, based on new technology titles in the MARC (MAchine Readable Cataloguing) records of the LOC for the annual series and on new technology publications listed in *PW* for the monthly series, do satisfy our requirements. In the

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[17] The turnover data represent unweighted medians of rates derived from the reports of samples of companies in non- seasonal industries and are based on the average number of wage earning employees on the payroll.

[18] For the inter-war period, they are, in any case, of limited use because the series is incomplete.

[19] See Griliches (1990).

[20] See Cyert and Mowery (1987), Griliches (1990), and Alexopoulos and Cohen (2009).

following sub-sections, we first describe the sources and the methods used to construct the indicators and then show that they offer compelling measures of technological innovation.

2.3.1. The Nature of the Indicators

The MARC records of the LOC are created by the Library to help run its online book search program and are also made available to other libraries to help them catalogue new books. The LOC is the depository library for the United States and is one of world's largest with over 130 items in more than 450 languages.[21] They, therefore, constitute a virtually complete list of new technology titles published each year in this country. Each MARC record contains information on the type of publication (for example, a new edition or a new title), place, language, library classification code, and a list of subjects treated in the volume. This information permits us to compile a list of all new technology titles published in the United States in English for the years 1909-49.[22] It also permits us to exclude books that focus on the history of technology, on home economics, and on handicrafts, none of which have much to do with technical advances in the private, non-farm economy. Finally, it enables us to create sub-series of new technological innovations for mechanical and manufacturing, electrical and electronic (including telecommunications), and automotive. The final compilation contains books and manuals that deal with all aspects of these new technologies from what they are and how they work to how to use and repair them. Some are published by the innovators, some by third parties – in all cases, the motivation is the same, to spread the word about the new device or technique and to reap financial gain by doing so.[23]

Annual indicators do have one potential drawback – they can mask some of the short run movements at business cycle frequencies. To deal with this problem, we created a series of indicators based on data drawn from *PW*, a weekly bulletin (with monthly

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[21] Although the LOC, 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/.

[22] For a full list of the T class categories and the components of our LOC indicator see Appendix A.

[23] See Alexopoulos and Cohen (2009) for further discussion of this notion.

summaries) published by R.R. Bowker. The volumes, intended for use by the procurement staff of libraries and book dealers, contain information by subject area on publisher (only major publishers are included), date and place of publication, language (mostly English), and type.[24] Indicators based on the *PW* lists cover a shorter time span than those constructed from the MARC records – they begin in 1920 – and are limited to aggregate estimates of innovative activity.[25] In spite of these limitations, they provide a useful compliment to the LOC series and allow us to determine if a change in observational frequency alters the results.

To recap, these new indicators are clearly consistent – the data on which they are based is gathered in exactly the same way by the same institutions for the same purpose every month or year during our period. They are objective – librarians and publishers identify the subject matter and other features of the volumes and have every incentive to get it right. They are easily quantified since they simply represent the total number of new technology publications by month (from major publishers) or by year (catalogued by the LOC). And, as we argue below, they have additional advantages: they capture innovations at the time of their commercialization, they give more weight to major as opposed to minor ones, and they include technologies, such as new management techniques, that are usually missed by patent or R&D measures.

2.3.2. Capturing Commercialization

As can be seen in Table 1, there is a close correspondence between the commercialization of an innovation as reported by Mensch (1979) or Jewkes, Sawers, and Stillerman (1969) and its first appearance in book form. Moreover, where discrepancies exist between book-based and subjective dating, the former often proves to be the more accurate of the two.[26] This correspondence between the first title releases and commercialization dates

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[24] Although the *PW* is limited to professional publishers, this group accounts for almost all books published in the U.S. To quote the publisher, "This list aims to be a complete and accurate record of American book publications."

[25] Included in the *PW* indicators are all technical publications encompassed by the Dewey classification numbers 600-609, 620629, 660-699.

[26] Consider, for example, the history of penicillin. Although the chemical and curative properties of the wonder drug were known for over a decade, our book dating indicator suggests that penicillin

makes perfect sense. Firms must promote their innovations – that's how they profit from them – and certainly in the period before WWII books and manuals were the natural way to disseminate the information. Independent writers and/or publishers – the major sources of literature on new technologies – have a similar motivation – spreading the word fosters adoption, stimulates demand for their books, and thus adds to their bottom line. For both groups, timing is crucial – too early, and no market is likely to exist for their titles, too late and the market is likely to be saturated and the information dated. In short, there is every reason to believe that new technology titles closely track the commercialization of new products and processes.

Statements made by publishers at the time confirm our supposition. As McGraw-Hill, a specialist in science and technology books, observed in a 1922 publication prepared for its authors, timing was critical: "From the standpoint of both the author and the publisher, it is desirable that a book …be put on the market as soon as possible after the manuscript is completed." A similar sentiment is expressed by Holliday and Van Rensselaer (1922) in *The Business of Writing* in which the authors note that the maximum time between the receipt of a manuscript and its acceptance is six months and, within nine months, the book should be available in bookstores. If considered urgent, as was often the case with technology titles, time to publication could be reduced to six months or less. Moreover, as Andrew Neilly Jr., former President of John Wiley and Sons reveals in Geiser (1985), publishers treat technical books differently – they frequently commissioned experts to write books on significant technical advances and used their stable of referees to provide quick assessment of the manuscript. In short, publishers made every effort to satisfy the inherent demand for these books as quickly as they could.[27]

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became a commercialized innovation in 1943. As it happens, prior to 1943, it was impossible to produce penicillin in quantities large enough to make it a viable product. A technological breakthrough (deep tank fermentation) enabled companies like Merck and Pfizer to take penicillin from the laboratory to factory floor, coincident with the first books on the new drug.

[27] Moreover, as Page (1905) points out publishers take great care to ensure that the books they publish will turn a profit. Failure to do so not only affects current revenue but also future profits since it impacts the ability of publishers to attract and retain the best authors.

There is, of course, the possibility that the book-based indicators chart diffusion not commercialization. Although possible, it is inconsistent with available evidence. In particular, if we were to assume, as seems plausible, that new product sales measure diffusion, then we would expect to observe a co-movement of book sales and our indicators if, in fact, the latter tracks diffusion. As the following examples illustrate, this was not the case.[28]

Consider first Streptomycin. The drug was initially commercialized and written about in late 1945. In September of that year, Merck, manufacturing the drug from a soil organism, managed to produce only 3000 grams. In 1947, Merck introduced a purified form (based on a calcium chloride complex) and output soared, going from 550, 000 g/month in June 1947 to 1,660,000 grams in December 1947. A new less toxic version, used for the treatment of tuberculosis, was released in limited supply at the end of October 1948. Production continued to expand exponentially, reaching 7.3 million grams in June 1949, over 20, 865, 000 grams by 1950, and, by 1966, 360,605,000 grams in the U.S. alone. New titles on the wonder drug, however, peaked in 1947 (the year the purified form was released) and quickly dropped to zero.

Plexiglas, a Rohm and Haas innovation, displays a similar pattern, one in which new titles on the product peak very early in the process, long before output takes off. The company introduced Plexiglas to the American market in late 1936, but it was only in1940 that the market for Plexiglas in aircraft and automobiles gained traction. Sales in constant 2005 dollars rose from $4.97 million in 1938 to $48.5 million in 1941 to over $190 million in 1965.[29] New titles, on the other hand, are concentrated in the period 1940-1942 with virtually no new ones since then even as output of Plexiglas has continued to expand.

2.3.3. Added Benefits

The T classification of the MARC records and the list of technical books in *PW* include, in addition to the usual process and product innovations, advances in scientific management and the organization of industrial production, breakthroughs that are largely not captured by R&D expenditures and patents. Books are published on these topics for the simple reason that someone – the author, the innovator- stands to gain from writing about

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[28] See also evidence in Alexopoulos and Cohen (2011).

[29] See Hochheiser (1986) for the nominal sales figures.

them.[30] A perfect case in point is Ford's moving assembly line, first introduced at the company's Highland Park plant on October 7, 1913, which cut production time per vehicle from 12.5 hours to 50 minutes.[31] In light of its economic importance, new titles were quick to follow. Less than a year later, for example, D. Appleton and Company's New York and London publishing houses released, "*Motor-cycle Principles and the Light Car, with explanations of the construction of those parts of motor cycles, cycle cars and the Ford car that differ from automobile practice, and chapters on care and maintenance, and on the location and remedy of trouble.*" Shortly thereafter The Engineering Magazine Company released a volume written by their experts entitled~~,~~ "*Ford methods and the Ford shops*." No patent or R&D statistics accurately identify the date of this advance and yet productivity jumped as a consequence and automobile production was transformed. For us, of course, the important feature is that it was picked up in print.

In addition to the extended range of coverage, our new indicators, because they are based on the number of new technology titles published each month or each year, give more weight to major than to minor innovations and, in a similar fashion, weight more heavily periods of intense as opposed to slack innovative activity. The reason is obvious. More books are likely to appear on major than on a minor innovations while more titles will be published if more new technologies, major or minor, are brought to market. This matters because it provides an objective way to weight innovations – something that other measures, with the exception of the citation based patent index developed by Jaffe and Trachtenberg (2002), are unable to do.

2.3.4. The indicators

As can be seen in Figure 1, the 1930s was indeed a technologically progressive period, with the largest number of innovations occurring in the latter half of the decade, coincident with the rapid increase in productivity. Moreover, the pattern of ups and downs differs across subgroups. For example, publications in electrical engineering undergo a sharp drop between 1929 and 1932 then experience an equally dramatic recovery through 1941. Manufacturing advances, on the other hand, begin their upswing a year later and continue

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

[31] See http://www.ford.com/about-ford/heritage/places/highlandpark/663-highland-park.

to expand fitfully through 1942. Finally, during the war years, the decreases in subgroups, such as automotive technologies, can be linked to the shift in focus from civilian to military-based innovations (whose titles are catalogued in another class).[32]

The observed variations across the indicators are significant for at least two reasons. First, they suggest that the measures represent more than mere trends in publishing and, in fact, do reflect differences in innovative activity across subgroups. Second, these differences permit us to distinguish between the impact on aggregate employment, for example, of new electrical technologies as opposed to those in machinery and thus to see if the nature of the technology has, as many claim, differing effects on labor demand.

2.3.5. Science and Technology

If our new indicators actually do represent, as we claim, compelling measures of technological change, we would expect to observe a causal relationship between advances in science (inputs into the production of some new technologies) and the new indicators (outputs of commercially viable new technologies) and also some correspondence between these indicators and other estimates of innovative activity. To see if these are, in fact, supported by the data, we ran the following bi-variate VAR[33];

$$Y_t = \alpha + \gamma_0 t + \gamma_1 t^2 + \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + \varepsilon_t \qquad (1)$$

where $Y_t = [\ln(Z_t), \ln(Tech_t)]'$, Tech is our LOC measure of aggregate technological change , and Z_t is one of Mensch's (1979) two indexes – either modern technical basic innovations or invention dates for the same major innovations – or one of three science indi-

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[32] Even the many publications that went along with technologies that were classified at the time (such as radar and atomic energy) can now be accessed. For example, the LOC's catalogue includes Philco Corporation's 1942 copyrighted manual on radar, "Instruction book for navy models ASG, ASG-1, aircraft radar equipment".

[33] We estimate the majority of the relationships in the paper using VARs in levels around a deterministic trend for two reasons. First, the KPSS and ADF tests produce conflicting results as to the presence of a unit root. Second, Gospodinov, Maynard and Pesavento (forthcoming) highlight problems associated with choosing a specification based on univariate unit root tests and demonstrate that severe biases can be introduced by removing low frequency movements by estimating VARs in first differences.

cators : (1) the number of journal articles reported in the Science Citation index; (2) the number of new U.S. titles in English in the field of science; or (3) the number of English language articles in the Inspec Archive Database (the major source for historical publications in the fields of physics, electrical and electronic engineering, communications, control engineering, and manufacturing and mechanical engineering).[34] Here we order our technology index last and use a Cholesky decomposition to identify the shocks.

In all cases we find a positive relationship between our indicators and these other metrics. Moreover, as the results reported in Table 2 demonstrate, both the indexes of scientific publications and Mensch's innovation dates Granger-cause our measures of technological change. Finally, based on our identification strategy, we find that all of the indicators explain a substantial share of the variance of our new technology index at 6 and 9-year horizons. In short, these results lend credence to our new indicators – they respond positively, as we would expect, to advances in science and move in tandem with at least one widely accepted measure of major innovations.

2.3.6. Trends or Tastes?

While it is, of course, possible that our publication-based indicators represent nothing more than trends in publishing (and thus have little if anything to do with the commercialization of new technologies), this appears to be inconsistent with the data. As can be seen in Figure 1, although book production overall does increase during this time period, new technology titles do not exhibit the same fluctuations as new titles in the technology sub-groups nor do they trace the same movements as books on music, fiction, and children's literature, none of which have anything to do with technological change. This would seem to suggest that short run changes in our publications-based measures, at the very least, are not driven by the exigencies of the publishing industry nor are they responding to same forces that affect other subgroups of the book trade.

A second possibility is that the observed swings in technology titles are driven not by changes in innovative activity as we contend but constitute, instead, responses by book

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[34] It should be noted that the first of these measures of scientific innovation is one of the metrics currently used by the National Science Foundation. To correct for changes in coverage, we normalize the number of articles by the number of journals covered each year in the database.

publishers to shifts in the public's taste for technical literature. However, if this were the case, it seems reasonable to assume that the public's new found appetite for such books would also show up in the demand for other types of technical publications such as those related to medical breakthroughs and/or advances in the natural sciences. However, as can be seen in Figure 1, fluctuations in the output of titles in these disciplines fail to mimic those in technology, thus suggesting that the changes are generally linked to supply and not demand.[35]

3. Employment and productivity

In this section, we use a series of bi-variate VARs to estimate the links between technological change (as measured by our indicators) and productivity or labor market variables using the following system:

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

where $Y_t = [\ln(Z_t), \ln(X_t)]'$, with Z_t representing one of our productivity or labor market variables, X_t one of our technology indicators (total, manufacturing and mechanical, electrical and electronic, automotive technologies or railroad) and E_{t-1} the log of high school graduates per capita in period t-1 (in an attempt to control for the effect of changes in education on publication trends, productivity and labor demand).[36] As in Shea (1998) and Alexopoulos (2011), we identify technology shocks by assuming that they affect the Z variables with a one period time lag for both the annual and monthly cases.[37]

We employ three sets of normalization techniques to control for changes in publication trends and/or tastes. In the first case, we deflate both the annual and monthly tech-

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[35] We return to these issues in the next section of the paper where books on music, children's literature, and medicine are introduced into the VAR equations. On the off chance that a more educated public has a more pronounced taste for technical literature, we also introduce into our regressions the number of high school graduates. The results suggest that this was not the case.

[36] Francis and Ramey (2004) also present results for VARs with a quadratic trend.

[37] To determine if ordering has a significant impact on our results, we also ran VARs with the Technology indicator entering before the productivity variables and found little evidence that it did. We have not included them in the paper but they are available on request.

nology series of by children's books (Norm 1)-to wash out general changes in the publishing industry. In an attempt to control for changes in the demand for technical books, we normalize our annual and monthly technology indicators first (Norm 2) with the number of medical titles and second (Norm3) – at annual frequencies - with the number of new titles in the field of natural science.[38]

3.1. Technological change and productivity

Since technical change exerts its influence on employment, at least in part, through its impact on productivity, it is necessary to explore first the relationship between technology as captured by our indicators and productivity during this period.

3.1.1. Aggregate productivity

In the first three rows of Table 3, we report the results of Granger causality tests for our aggregate measures of technical change and productivity. For the annual analysis, we use the standard TFP and labor productivity measures, while for the monthly cases, we use our two labor productivity series - the first for the aggregate economy for the period January 1929 – December 1949 and the second for the manufacturing sector for the period January 1920 – December 1949.[39]

As can be seen, for both annual and monthly data, our technology indicators clearly Granger cause changes in labor productivity at both annual and monthly intervals (and TFP for annual data) and are for the most part significant at the 5 - 10% levels for all normalized versions of the indicators. Although there is little evidence in the annual data to indicate reverse causality, that is, from productivity to technology, at monthly frequencies causality seems to run in both directions.

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[38] In an earlier version of the paper we reported findings for the case with no normalizations. The qualitative results are unchanged from those presented here and the quantitative results for the variance decomposition exercises generally fall between the magnitudes reported for Norm1, and Norm2. Since PW does not break out titles on natural science, we cannot use Norm 3 for the monthly series.

[39] The dates are determined by data availability

In the first panel of Table 4, we present variance decompositions at annual frequencies for all three normalizations for GNP per employee and for private non-farm TFP at 3, 6, and 9-year horizons and for Norms 2 and 3 for the monthly productivity measures. A few features of these results merit attention. First, the variance attributable to the new indicators is somewhat smaller for labor productivity than for private non-farm TFP. Second, of the three normalizations, that of medicine gives the weakest results, not surprising given that a large number of medical advances also occurred during this period.[40] Third, the relationship between technical change and productivity is much stronger at monthly than at annual frequencies, a consequence of the prominent role played by major, commercially oriented publishers in the *PW* series, since these accounted for a disproportionate share of titles on influential and widely used innovations.[41]

Figure 2 presents the impulse responses to a 1% positive technology shock along with 90% confidence bands for GNP per employee and TFP at annual frequencies and for both industrial production and manufacturing output per employee. As we might expect, the standard errors are larger for the annual than for the monthly data but in both cases and for all normalizations, the relationship between technical change and productivity is positive, and, in most cases significant, peaking between one and two years following the initial shock.

3.1.2. Productivity and General Purpose Technologies

It is often argued that general purpose or near general purpose technologies are of particular interest because of their widespread impact across a broad range of products and processes. (See e.g., Helpman (1998)) As it happens, a significant number of major breakthroughs occurred during our period in Electrical/Electronics, Machinery, and Automotive, areas often associated with GPT or near-GPT.[42] The question is whether the effect of these

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[40] See Albanesi and Olivetti (2009) for a paper discussing some of these innovations.

[41] Alexopoulos (2011) also finds that the annual indicators reported by R.R. Bowker's for the post war period have a stronger impact on productivity than the aggregate measures derived from the LOC.

[42] It should be noted that while Jovanovic and Rousseau (2005) date the end of the GPT-era for Electrification in 1929, our more broad based definition of the sector extends it into the 1940s.

innovations can be seen in the data, that is, do GPT or near-GPT exhibit a distinctive impact on productivity during these years? To get at this relationship, we explore the link between productivity and technology shocks tied to advances in these three areas. Since the monthly figures from PW cannot be broken down by fields, we use only the annual indicators from the LOC for this purpose.

As can be seen in Tables 3 and 4, innovations in these areas Granger-cause annual productivity (often at the 1% level) and their impact on productivity is large. Of even greater significance, as can be seen in Table 4, the percent of the variance in aggregate productivity accounted for by the three GPT or near GPT fields is much larger than that attributable to the aggregate technology indicator. Thus, while 5 to 10 percent of the variation in aggregate labor productivity and 5 to 27 percent of the variation in TFP is attributable to the LOC aggregate technology indicator, the magnitudes increase dramatically to between 14 and 30 percent for GNP per employee and 13 to 39% for TFP when the manufacturing/mechanical indicator is used, 9 to 18% and 8 to 25% when the electrical indicator is utilized and 10 to 34% and 9 to 36% when the automotive index is employed.

The disaggregated impulse-responses presented in Figure 3 show the response of productivity to a 1% positive technology shock at 90% confidence intervals. As can be seen, productivity significantly rises for all cases considered. Responses to an automotive or mechanical/manufacturing shock peak two years after the shock while the maximum response to an electrical/electronics shock occurs in the first year.[43]

3.2. Labor market responses to technical change

We now turn to the central focus of this analysis: the relationship between our indicators of technical change and employment/unemployment during this period. Using the annual data, we examine the responses of employment (Total, Manufacturing, and Transportation), total hours, and unemployment to a variety of technology shocks. At the monthly frequency, we utilize the *PW* indicator along with a variety of labor market variables (vacancies, unemployment, employment, hours, quits, layoffs, dismissals and ac-

[43] Since our indicators pick up the commercialization of the GPT and GPT related technologies, our measures relate to the boom period (Phase 2) identified in the theories advanced by Aghion and Howitt (1998) and Helpman and Trajtenberg (1998).

cession rates) to provide a more complete picture of the impact of technical change on the labor market during this period.

3.2.1. The labor market's responses to technical change at the aggregate level

Annual variables- In Table 5 we report the results of the Granger-causality tests at annual frequencies for aggregate employment per capita, aggregate unemployment per capita, per capita non-farm employment, private non-farm hours per capita, manufacturing employment and transportation employment. While our results suggest the presence of a weak relationship between our LOC aggregate technology measure and aggregate employment, unemployment, and hours, they also reveal that our aggregate technology indicator does Granger-cause fluctuations in manufacturing and transportation employment.

Impulse responses to a 1% positive technology shock are reported in Figures 4 and 5. Most telling, we find that no matter which measure of employment or unemployment we use or which sector we focus on, we fail to uncover any evidence that technology shocks caused employment or hours to fall or unemployment to increase. Instead, our results suggest that, on the whole, employment opportunities increased in response to a positive technology shock and unemployment fell – even in the short run. As such, these outcomes are consistent with the neoclassical model's predictions regarding the effect of technological change on employment and hours.

The variance decompositions at 3, 6, and 9-year horizons for these variables are presented in Table 6. The results based on Norm1 or Norm3 suggest that approximately 10 percent of the variation in the aggregate labor market variables, 16 percent of manufacturing employment variation and as much as 27 percent of transportation employment fluctuations are attributable to technical change at the six year horizon, while the estimates obtained employing Norm2 indicate a more limited role for the innovations.

Monthly variables- As the results in Table 7 confirm, our new monthly technology indicators Granger-cause movements in aggregate non-farm employment, manufacturing hours and employment, the unemployment rate, as well as a number of labor market variables including aggregate vacancies, and the median layoff, discharge, quit, separation and accession rates in the manufacturing sector. Furthermore the impulse responses depicted in Figures 6 and 7 demonstrate that the responses of the monthly labor market variables during this period are consistent with the predictions of neoclassical type search model in that technological change creates both job opportunities and greater turnover among the workers.

The responses of aggregate employment, manufacturing hours and employment, the unemployment rate and the vacancy index to a 1% positive technology shock is illustrated, along with 90% confidence intervals, in Figure 6. Overall, we find no evidence that hours or employment decrease in the short run. In fact, they tend, overall, to rise within the first quarter following the shock, coincident with a drop below trend in the unemployment rate, and an increase in advertised vacancies.

In Figure 7, we illustrate the effects of technology shocks on labor turnover in the manufacturing sector from 1920-1949. We find that a positive technology shock causes quits, discharges, and the median accession and separation rates to increase, and layoffs to decrease. In short, the evidence would seem to suggest that while a positive technology causes an overall increase in jobs, innovations also seem to foster, as manifest in the dissolution of the employment relationships, a mismatch between the skills of some of the existing workers and the new work environment. As the WPA reports highlight, many of these breakups occurred because workers were not adept at using the new technologies or were unwilling or unable to be retrained.[44]

Finally, the results presented in Table 8 suggest that our monthly indicators of technological innovation account for a significant share of the variance for all labor market variables at all horizons and for both normalizations. A few of these results are of particular interest because of the light they shed on the connection between new technologies and employment. First, the very strong relationship between vacancies (job postings) and innovation indicates that technological change, on the whole, was responsible for many of the new employment opportunities. Second, the large share of the variations in layoffs,

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[44] For example, Evans (1939) notes that while the new cigar rolling technology displaced existing workers, it also created opportunities for new hires with the skills necessary to run the machines. Hence it would be incorrect to infer from this that the new technology simply required workers with higher (or for that matter lower) skill levels. It simply necessitated employees with a different set of skills.

quits, and discharges explained by our technology indicators lends further credence to the notion that the new technologies, while they did create jobs, may also have contributed to the labor market turbulence experienced by workers.

3.2.2. Labor market responses to GPT and near-GPT innovations

Although productivity was significantly affected by changes in these technology groups, they did not have a uniform impact on labor inputs or unemployment. In particular, while technical change in the automotive and electrical/electronics fields Granger caused changes in these variables (See Table 5), with the exception of transportation employment, there is virtually no evidence that manufacturing/mechanical innovations significantly affected employment, hours, or the number of workers seeking employment.

There are also a few features of the variance decompositions reported in Table 6 worth noting. First, while the different GPT technologies had similar impacts on productivity, their quantitative resonance in the labor market was not the same. In keeping with the results reported above, new automotive and electrical technologies explain a significant share of the variations in employment, hours and unemployment at 3, 6, and 9-year horizons across all labor market variables and, for the most part, for all normalizations. Specifically, the shares at the 6-year horizon for the case of electrical technologies range from 6 to 18.4 percent for aggregate labor input measures, 9 to 14 percent for unemployment, 6.6 to 18.2 percent manufacturing employment and 7.5 to 19.4 percent for transportation employment. For automotive technologies, the comparable numbers for the upper bounds are 1.5 to two times larger (based on Norms 1 and 3) with the lower bound (based on Norm2) increasing two-threefold for the aggregate series with the ranges rising to 25.5 to 39 percent for manufacturing and 31 to 44 percent for transportation employment. In contrast to these results, the percentage of fluctuations attributable to technical change in manufacturing/machinery is far smaller for aggregate employment and hours across these horizons, even though there is some evidence that the relationship between these innovations and movements in transportation employment, unemployment, and manufacturing employment are of a similar magnitude to those seen for the case of electrical technologies.

The impulse responses to a 1% positive technology shock along with the 90% confidence intervals are shown in Figure 8A-C. They confirm that the labor market responded differently to the various types of technology shocks. As shown in Panel 8A, for example, aggregate employment significantly rises following a technology shock in both electrical/ electronic and automotive, in the former case the effect lasts five years and peaks after one or two periods, in the later, the peak is reached in two or three years. In contrast, the hypothesis that aggregate employment is unaffected by a technology shock in manufacturing/mechanical cannot be rejected.

In Panel 8B, the impact of technology shocks on total hours and unemployment is depicted. The point estimates indicate that per capita hours go up and unemployment falls, in many instances significant even in the short run. A comparison of Panels 8A and 8B for the various cases reveals that total hours worked rise more than employment, suggesting technology shocks also cause hours per employee to increase. Finally, in Panel 8C, the employment response in manufacturing and transportation are displayed. In all cases bar one (manufacturing employment following a manufacturing/mechanical shock), responses are positive with most of them significant for all normalizations.

An obvious question: Why does the impact differ so noticeably across the various sources of the shocks? Provision of a complete answer to this question exceeds the scope of the current paper but, we believe the answer is likely to reside in the differing impact of product and process innovations on labor demand. It is important to note, first, that GPT and near-GPT technologies, by definition, lead to advances in both these areas across a variety of sectors. Second, as shown in the industrial organization literature, product innovations are, on the whole, labor using (see, for example, Harrison et al (2008) and Spiezia and Vivarelli (2002)) while process ones are often moderately labor saving (see Doms, Dunne and Roberts (1995), Blanchflower and Burgess (1999), and Ross and Zimmerman (1993)). Third, and related, as Harrison et al (2008) note, while a process innovation may displace workers because of its labor-saving nature, it may also stimulate demand to the extent that the cost savings are passed on to consumers though lower prices. Thus, the sign of the employment response to the innovation depends crucially on the relative magnitude of each of the effects. With these observations in mind, it would appear that electrical and automotive advances included many new products while manufacturing/machinery innovations embodied relatively more process innovations.[45] In short, our results suggest that variation in the employment response of the sectors may be a consequence of differences in the relative mix of product and process technologies in each area. This, we believe, is a potentially fruitful area for future research.

3.3. Sensitivity Results

In this section, we report the results of a number of sensitivity checks to show that the findings recorded above are robust. We use in these VARs our monthly indicators to maximize the number of observations and report the impulse responses of aggregate employment and manufacturing employment to a 1% aggregate technology shock along with 90% standard error bands. The results are presented in Figure 9.

We isolate first the 1930s since there are a number of reasons why the relationship between employment and technological change might be different during the Great Depression. First, both the "roaring twenties" and the war years were boom times in the U.S. and as they account for a large share of our sample, they may be driving our results. Second, as Cole and Ohanian (2004) point out, New Deal legislation fostered major changes in the nature of the wage bargain and in the degree of competition, either or both of which could have caused alterations in the relationship between technological change

[45] Although all of these technology groups ushered in changes in production processes, they differed noticeably in their impact on new products. Thus while technological advances in both electrical machinery and in manufacturing/machinery led to the creation of new products for use in manufacturing, the range of new products associated with the former far exceeded those of the latter. For example, a host of new electricity based consumer products including small and large household appliances, radios, etc. appeared during this period. Job growth directly linked to these occurred in wholesale and retail trades, transportation, and services. Demand for these goods, which jumped 2 to 3 fold between 1929 and 1941, also expanded work for electricians and others in the building trades since, among other things, homes often had to be rewired to facilitate adoption of the new products. (See Tobey (1996)). The diffusion of the radio created whole new industries (broadcasting, entertainment, news) or reshaped old ones (advertising) – and, of course, lots of new jobs. Overall, the employment impact of these new consumer products appears to have been quite dramatic.

and employment. Third, some New Deal regulations 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.[46] Although no consensus exists concerning the impact of these new rules on economic activity, they certainly could have altered the relationship between employment and technology shocks.[47] As can be seen in the first panel of Figure 9, in spite of the fact that the standard errors rise, employment opportunities do increase following a technology shock, an indication that the neoclassical benchmark model, even with all the changes in the 1930s, is consistent with the empirical evidence.

In our second robustness check, we expand the number of variables in the VAR to include the short run commercial paper rate and the log of the CPI. Following the literature on monetary policy shocks, we order the employment variable before the interest rates and prices and maintain our assumption that technology only impacts the economy with a one period lag (in this case one month). As shown in panel B of Figure 9, both manufacturing and aggregate employment rise significantly in response to the positive shock in the short run.

In our third test, we first difference the employment series. As is well-known, the results based on the long-run identification method change depending on whether the per capita labor input series enters the VAR in first differences or in log levels. As the work of Fernald (2007) and Gospodinov et al (forthcoming) indicate, this is likely a consequence of the low frequency co-movement between hours and labor productivity growth. Although our short run identification method may be less sensitive to this co-movement (see Goso-

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[46] For example, 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) - the agency empowered to carry out these provisions - thirty-six of them "contained restrictions on the installation of new machinery and on increase in productive capacity". See also the July 8, 1934 article in the New York Times, entitled "Capital Industries Affected by Codes", Bernstein (1987) and Hawley (1964) for more details concerning the regulations on different sectors.

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

podinov et al (2009)), we, nevertheless, reran the VARs with employment entering in first differences. The results, as reported in Panel C of Figure 9, show that even in first differences, employment expands following a positive technology shock.

4. 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 development expenditures, and innovation counts are dogged by a variety of problems. We develop in this paper new indicators of technical change that, we believe, are exempt from most of these difficulties and use them to explore the relationship between innovation and employment for the period 1909-49. Our findings help inform model selection and clarify the role of technical change in cyclical fluctuations.

To summarize our results briefly, we observe a positive relationship between technology shocks and employment at both annual and monthly frequencies. The results are, in some instances, affected but not eliminated or overturned by the normalization method adopted. In other words, our metric is not simply an artifact of the publishing trade or a reflection of preferences for technical books. We also find that technical change in some areas – electrical and automotive – had a much more powerful impact on employment than in others – manufacturing and all technologies. Finally, new technologies were associated with a jump in vacancies, and in accession and separation rates – all of which go along with a technology induced increase in turnovers. 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).

Finally, our findings indicate that while the technologies associated with the GPTs and near GPTs (electrical, automotive, and mechanical innovations) had similar impacts on productivity during the period, they differed in their impact on employment. One possible explanation is that each group contains a different mix of product (labor using) and process (or labor saving) innovations. Verification of this hypothesis is left for future research.

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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

Table 1: Comparison of Invention and innovation dates, with Commercialization Dates and LOC First Book Dates

Invention	Date of Invention	Mensch's Date of Innovation	Date of Commercialization	LOC Book Date
Diesel-electric locomotive	1895	1925	1925	1926
Insulin	1889	1922	1922	1922
Neoprene/Duprene	1906	1932 (Duprene) 1937 (Neoprene)	1932	1937
Nylon	1927	1938	Dec. 1939	1939^
Penicillin	1928	1941	1943	1943
Radio*	1887	1922	1920 – 1922	1920
Streptomycin	1921	1944	1945	1945
Automatic Transmission	1904	1939	1939	1939
Kodachrome	1910	1935	1935/1936	1937
Tungsten Carbide	1900	1926	1930	1930
Silicones	1904	1946	1946	1946
Scientific Management (Tayor)	1910	n/a	1911	1911
Time in Motion Studies (Gilbrath)	1911	n/a	1911	1911
Industrial and General Administration (Fayol)	1918 (in France)	n/a	Early 1930s	1930 (UK English printing)
Quality Control	1922-24	n/a	1924	1922

Sources: Mensch's (1979), Jewkes et al (1969), http://inventors.about.com., and Library of Congress.
Notes: ^ 1940 is the first new English language title.
*Here the innovation date chosen by Mensch refers to the development of equipment using short waves for transmission over long distances. However, the radio sets and commercialization of radio broadcasting occurs between 1920 and 1922. The LOC book date and Amazon dates are the first books related to broadcasting and the receiving sets. The first broadcasts occurred in 1920 one of which was Westinghouse's KDKA-Pittsburgh broadcast of the Harding-Cox election returns.

Table 2. Relationship between Science and Technology

Science indicator	Does the Science & Mensch indicators granger-cause the Technology indicator? (P-value)	Does the Technology indicator granger-cause Science & Mensch indices? (P-value)	horizon (years)	% of Technology variance attributable to Science & Mensch indices
			3	19.74
Science Citation Index	0.0200	0.0000	6	26.19
			9	25.90
			3	38.64
New Science Titles	0.0007	0.0019	6	45.92
			9	43.71
			3	3.37
Inspec journal articles	0.0003	0.0000	6	12.17
			9	16.09
			3	11.45
Mensch Invention Index	0.0331	0.6935	6	12.02
			9	12.22
			3	19.35
Mensch Innovation index	0.0004	0.4467	6	24.73
			9	25.41

*Results are based on bi-variate VARs using annual data with two lags of each variable included and a quadratic trend. Reported variance decompositions are based on the case where the book-based technology indicator is ordered last.

Table 3: Granger causality tests

Do the technology indicators Granger Cause labor productivity or TFP?

Indicator		Aggregate Y/E ($1947)	TFP private non-farm (1947)	I.P/Emp (monthly)	I.P./Emp in Manufacturing (monthly)
All Technology	(1)	0.125	0.009	0.030	0.175
	(2)	0.096	0.063	0.010	0.002
	(3)	0.050	0.016	n.a.	n.a.
Manufacturing	(1)	0.005	0.001	n.a.	n.a.
	(2)	0.008	0.003	n.a.	n.a.
	(3)	0.012	0.001	n.a.	n.a.
Electrical	(1)	0.001	0.001	n.a.	n.a.
	(2)	0.011	0.025	n.a.	n.a.
	(3)	0.013	0.015	n.a.	n.a.
Automotive	(1)	0.054	0.018	n.a.	n.a.
	(2)	0.040	0.027	n.a.	n.a.
	(3)	0.037	0.012	n.a.	n.a.

Do the productivity variables Granger Cause the technology indicators?

Indicator		Aggregate Y/E ($1947)	TFP private non-farm (1947)	I.P/Emp (monthly)	I.P./Emp in Manufacturing (monthly)
All Technology	(1)	0.539	0.744	0.000	0.000
	(2)	0.450	0.362	0.008	0.103
	(3)	0.874	0.663	n.a.	n.a.
Manufacturing	(1)	0.492	0.568	n.a.	n.a.
	(2)	0.880	0.936	n.a.	n.a.
	(3)	0.680	0.756	n.a.	n.a.
Electrical	(1)	0.077	0.156	n.a.	n.a.
	(2)	0.176	0.442	n.a.	n.a.
	(3)	0.425	0.592	n.a.	n.a.
Automotive	(1)	0.038	0.079	n.a.	n.a.
	(2)	0.078	0.192	n.a.	n.a.
	(3)	0.147	0.264	n.a.	n.a.

Notes: (1), (2) and (3) indicates that the results reported in the corresponding rows are based on the indicator normalized by children's titles (Norm1), medical titles (Norm2), and natural science titles (Norm3) respectively.

Table 4: Variance decompositions for Productivity Measures

Indicator	Horizon	GNP per employee ($1947)			Private Non-Farm TFP (1947)			I.P./EMP		Manufacturing I.P./Emp	
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(1)	(2)
	3 year	4.8	6.0	6.5	14.1	5.6	8.6	48.67	39.67	23.99	22.91
All Technology	6 years	9.0	7.7	9.6	24.7	7.1	12.0	49.74	40.68	25.31	24.42
	9 years	10.4	8.2	10.3	27.3	7.4	12.6	49.77	40.78	25.30	24.47
	3 years	14.4	17.8	16.1	21.6	13.0	17.3	n/a	n/a	n/a	n/a
Manufacturing	6 years	26.0	27.8	26.6	35.8	20.5	26.7	n/a	n/a	n/a	n/a
	9 years	28.9	30.0	28.7	38.4	21.9	28.1	n/a	n/a	n/a	n/a
	3 years	13.4	9.6	11.7	19.5	8.1	12.7	n/a	n/a	n/a	n/a
Electrical	6 years	17.1	10.7	16.4	23.7	8.9	16.8	n/a	n/a	n/a	n/a
	9 years	17.7	10.9	17.2	24.1	9.0	17.3	n/a	n/a	n/a	n/a
	3 years	10.8	13.1	13.6	13.1	9.7	14.1	n/a	n/a	n/a	n/a
Automotive	6 years	26.9	24.4	24.7	31.0	18.2	24.2	n/a	n/a	n/a	n/a
	9 years	33.2	27.4	27.4	35.8	20.1	25.8	n/a	n/a	n/a	n/a

Notes: (1), (2) and (3) indicates that the results reported in the corresponding column are based on the indicator normalized by children's titles (Norm1), medical titles (Norm2), and natural science titles (Norm3) respectively.

Table 5: Granger-causality tests

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

Indicator		Aggregate employment	Aggregate un-employment	Private Non-Farm Em-ployment	Private non-farm hours	Manufacturing Employment	Transportation Employment
All Technology	(1)	0.230	0.215	0.158	0.209	0.036	0.002
	(2)	0.657	0.205	0.553	0.386	0.173	0.006
	(3)	0.268	0.034	0.056	0.053	0.002	0.005
Manufacturing	(1)	0.568	0.143	0.445	0.386	0.183	0.005
	(2)	0.581	0.202	0.803	0.786	0.943	0.045
	(3)	0.619	0.053	0.199	0.140	0.026	0.004
Electrical	(1)	0.019	0.002	0.007	0.005	0.000	0.005
	(2)	0.013	0.003	0.007	0.001	0.001	0.024
	(3)	0.040	0.000	0.005	0.002	0.000	0.005
Automotive	(1)	0.087	0.118	0.064	0.036	0.017	0.002
	(2)	0.097	0.094	0.083	0.032	0.017	0.003
	(3)	0.111	0.026	0.071	0.044	0.020	0.004

Do the productivity variables Granger Cause the technology indicators?

Indicator		Aggregate employment	Aggregate un-employment	Private Non-Farm Em-ployment	Private non-farm hours	Manufacturing Employment	Transportation Employment
All Technology	(1)	0.458	0.909	0.576	0.501	0.898	0.181
	(2)	0.309	0.061	0.283	0.376	0.009	0.638
	(3)	0.870	0.954	0.810	0.915	0.683	0.714
Manufacturing	(1)	0.949	0.937	0.770	0.978	0.336	0.282
	(2)	0.148	0.302	0.151	0.250	0.012	0.763
	(3)	0.901	0.891	0.997	0.967	0.609	0.568
Electrical	(1)	0.212	0.180	0.211	0.116	0.397	0.077
	(2)	0.910	0.390	0.856	0.534	0.717	0.719
	(3)	0.604	0.437	0.467	0.419	0.509	0.488
Automotive	(1)	0.056	0.263	0.090	0.053	0.463	0.007
	(2)	0.374	0.427	0.277	0.159	0.938	0.106
	(3)	0.248	0.353	0.136	0.078	0.550	0.062

Notes: (1), (2) and (3) indicates that the results reported in the corresponding rows are based on the indicator normalized by children’s titles (Norm1), medical titles (Norm2), and natural science titles (Norm3) respectively.

Table 6: Variance Decomposition for Annual Labor Market Variables

Indicator	Horizon	Aggregate per capita Employment			Aggregate per capita Unemployment			Private per capita Non-farm Employment			Private per capita Non-farm hours			Per capita Manufacturing Employment			Per capita Transportation employment		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
All Technology	3 year	6.0	0.5	1.8	4.5	4.0	5.9	6.9	0.7	6.5	4.4	1.4	6.8	9.4	1.9	11.9	15.8	9.6	10.9
	6 years	10.3	0.6	2.6	7.8	4.8	8.3	12.6	0.9	9.2	8.3	1.9	9.8	16.2	2.2	15.6	27.5	12.2	16.0
	9 years	11.0	0.6	2.8	8.4	4.9	8.7	14.2	1.0	9.6	9.5	2.0	10.4	18.2	2.3	16.3	30.6	12.9	17.3
Manufacturing	3 years	1.1	0.5	0.5	6.6	5.8	8.9	1.8	0.1	4.1	1.9	0.2	5.8	3.6	0.0	11.2	14.3	7.8	13.8
	6 years	2.1	0.9	0.9	11.4	8.9	14.7	3.7	0.2	7.4	4.0	0.3	10.4	6.4	0.0	16.9	26.3	13.5	24.0
	9 years	2.3	1.0	1.0	12.4	9.5	15.6	4.3	0.3	8.2	4.8	0.3	11.7	7.3	0.0	18.0	29.9	15.4	26.7
Electrical	3 years	12.9	5.5	5.6	11.3	8.1	9.6	14.7	6.4	11.1	12.5	7.1	11.6	14.3	5.9	13.7	14.9	6.6	11.5
	6 years	15.6	6.0	7.5	14.0	9.0	13.1	18.4	7.1	14.7	15.8	7.9	15.7	18.0	6.6	18.2	19.4	7.5	16.5
	9 years	15.7	6.0	7.7	14.2	9.1	13.5	18.8	7.2	15.1	16.3	8.0	16.2	18.6	6.8	18.8	20.4	7.8	17.7
Automotive	3 years	10.8	9.0	8.3	8.4	9.9	11.9	10.8	8.2	12.4	12.0	11.9	14.7	16.9	14.0	24.8	19.5	16.9	19.6
	6 years	24.5	16.1	14.3	20.2	18.2	20.4	26.3	15.7	21.5	29.3	22.3	25.7	38.8	25.5	37.8	44.0	31.1	34.1
	9 years	27.0	17.3	15.0	23.4	19.8	21.6	31.0	17.4	22.7	35.2	25.0	27.6	46.0	28.9	39.6	50.8	35.3	37.3

Notes: (1), (2) and (3) indicates that the results reported in the corresponding column are based on the indicator normalized by children's titles (Norm1), medical titles (Norm2), and natural science titles (Norm3) respectively.

Table 7: Granger-causality tests

Do the technology indicators Granger Cause movements in labour market variables?

Variable	Technology/Childrens Titles	Technology/Medical Titles
Aggregate Non-Farm Employment	0.009	0.003
Hours in Manufacturing Sector	0.018	0.054
Employment in Manufacturing Sector	0.012	0.083
Unemployment rate	0.001	0.001
Vacancies	0.034	0.003
Median Layoffs per 100 workers in Manufacturing	0.028	0.005
Median Discharges per 100 worker in Manufacturing	0.175	0.024
Median quits per 100 workers in Manufacturing	0.001	0.035
Median total Separations per 100 workers in Manufacturing	0.029	0.008
Median Gross Accession per 100 workers in Manufacturing	0.034	0.878

Do the labor market variables Granger-Cause the technology indicators?

Variable	Technology/Childrens Titles	Technology/Medical Titles
Aggregate Non-Farm Employment	0.018	0.000
Hours in Manufacturing Sector	0.015	0.070
Employment in Manufacturing Sector	0.271	0.000
Unemployment rate	0.383	0.097
Vacancies	0.001	0.075
Median Layoffs per 100 workers in Manufacturing	0.000	0.000
Median Discharges per 100 worker in Manufacturing	0.000	0.000
Median quits per 100 workers in Manufacturing	0.000	0.000
Median total Separations per 100 workers in Manufacturing	0.143	0.000
Median Gross Accession per 100 workers in Manufacturing	0.000	0.012

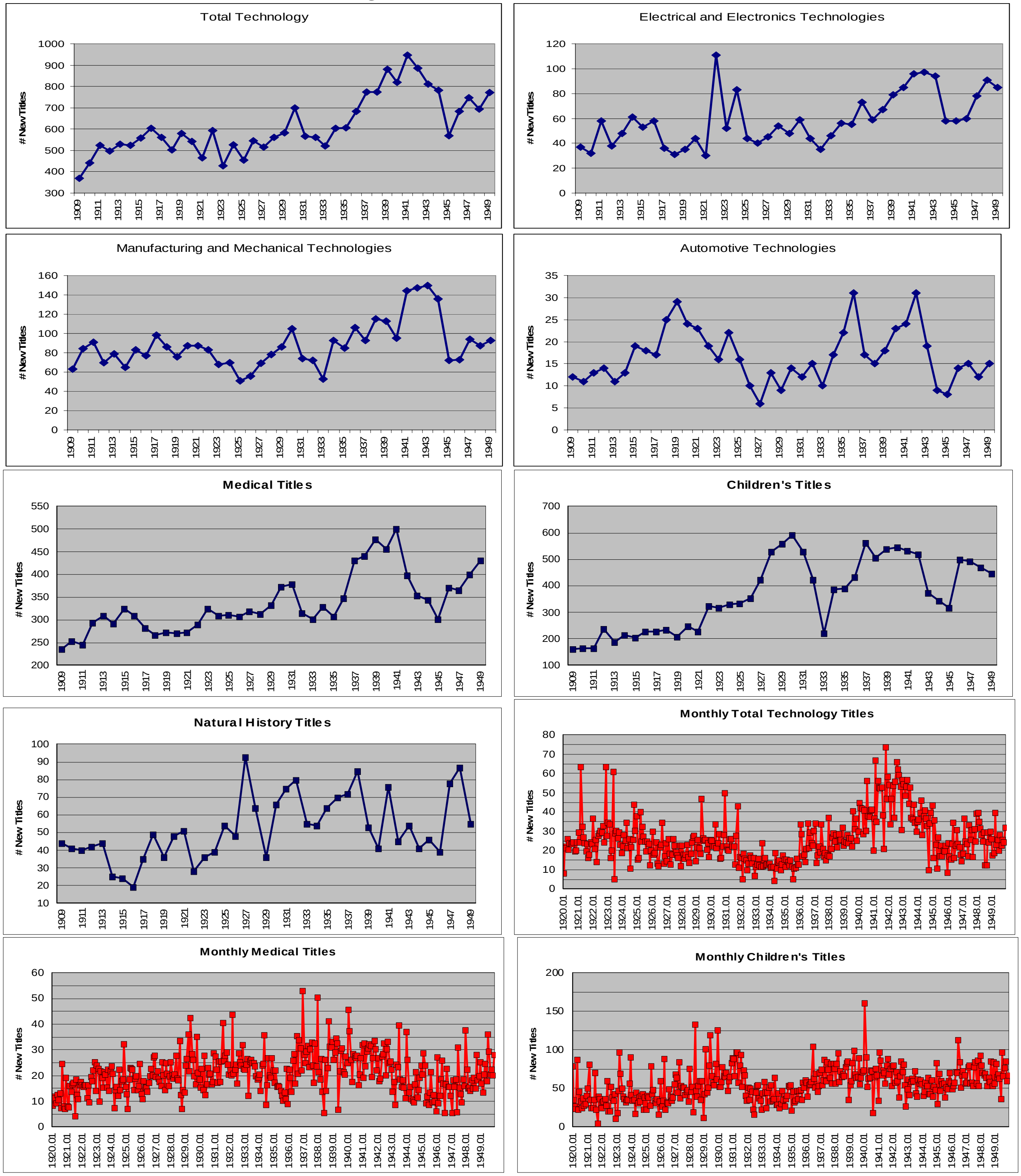
Table 8: Variance Decomposition for Monthly Variables

Horizon	Aggregate Non-Farm Employment		Employment in Manufacturing Sector		Hours in Manufacturing Sector		Unemployment rate		Vacancies	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
3 years	19.03	27.76	38.39	24.82	35.95	27.05	29.85	44.14	59.45	41.11
6 years	21.82	28.34	42.29	26.41	41.02	29.38	33.93	45.35	62.79	49.68
9 years	21.82	28.34	42.30	26.48	41.03	29.52	33.97	45.39	62.84	50.63

Horizon	Median Layoffs per 100 workers in Manufacturing		Median Discharges per 100 workers in Manufacturing		Median quits per 100 workers in Manufacturing		Median total Separations per 100 workers in Manufacturing		Median Gross Accession per 100 workers in Manufacturing	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
3 years	19.34	17.97	21.93	18.90	35.70	29.75	24.79	17.48	16.84	9.27
6 years	19.60	18.44	21.74	18.79	36.06	29.91	24.91	17.68	16.64	9.20
9 years	19.60	18.47	21.71	18.78	36.06	29.92	24.92	17.69	16.61	9.19

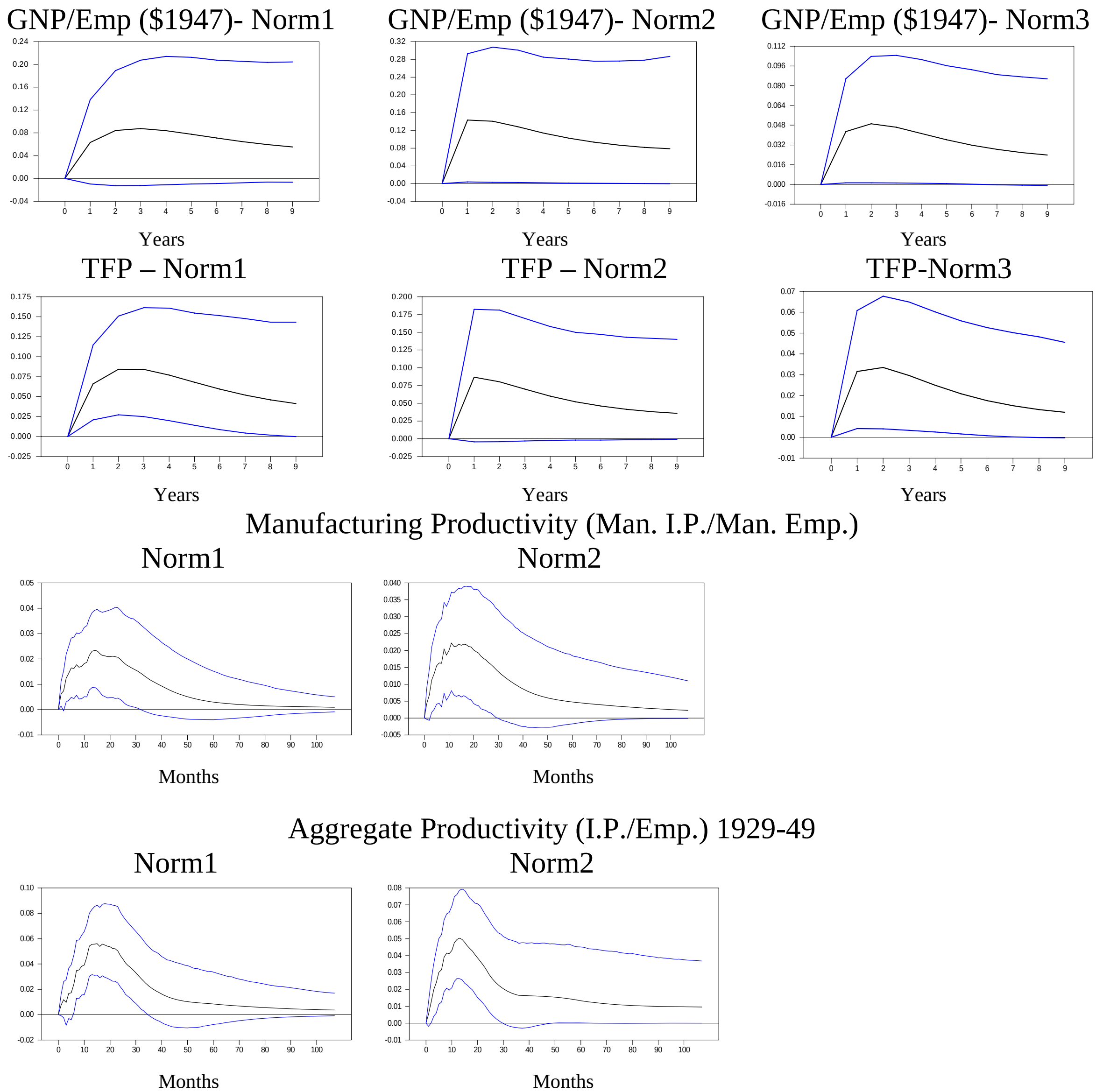
(1) Indicates the case technology is normalized by children's titles (Norm1).
(2) Indicates the case technology is normalized by medical titles (Norm2).

Figure 1: The Book-Based Indicators



Source: Annual series are based on the Library of Congress' MARC record database. Monthly series are based on book lists in issues of Publisher's Weekly from January 1920- December 1949.

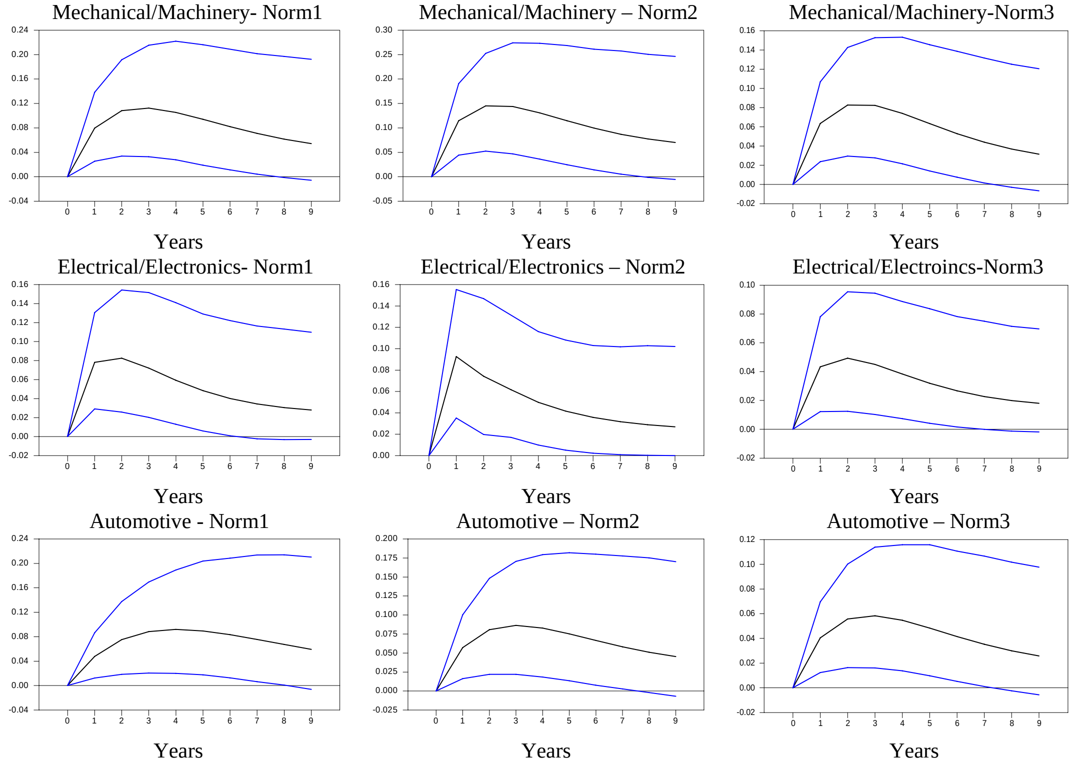
Figure 2. Impulse responses to an aggregate technology shock – Productivity measures



Notes: Norm1, Norm2 and Norm3 correspond to the cases where the technology indicator was deflated by children's titles, medical titles, and natural science titles respectively.

Figure 3. Productivity Responses to Disaggregated Technology shocks

GNP per Employee ($1947)



Total Factor Productivity

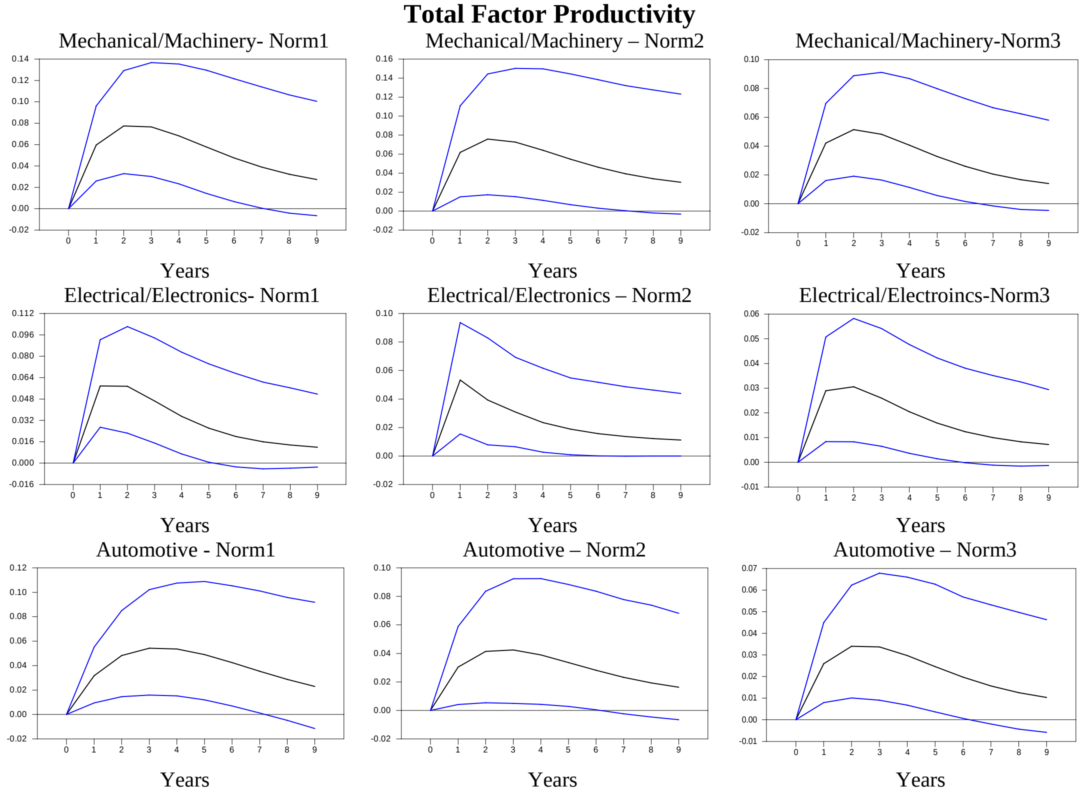


Figure 4: Aggregate Employment and Hours Responses to an Aggregate Technology shock (LOC case)

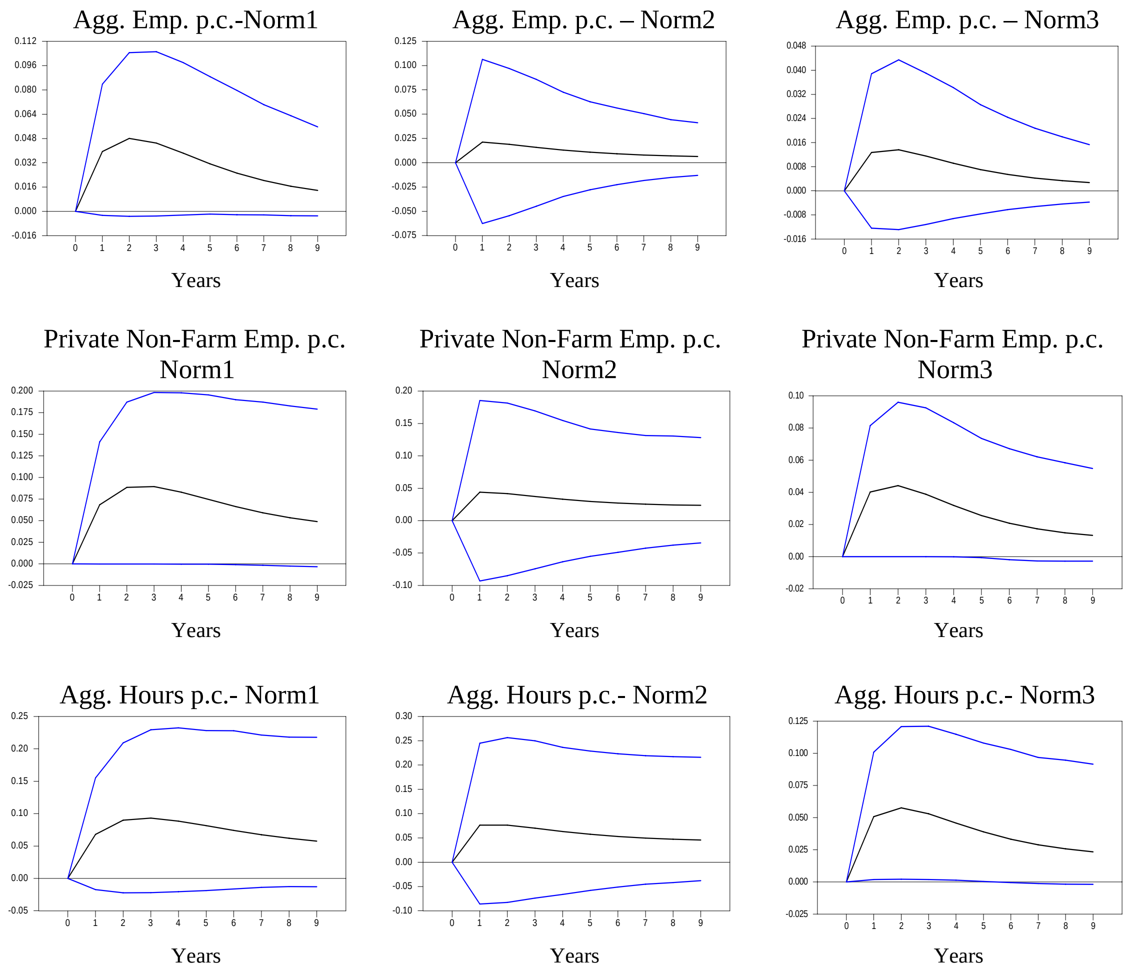


Figure 5: Unemployment, Manufacturing Employment, and Transportation Employment Responses to an Aggregate Technology shock (LOC case)

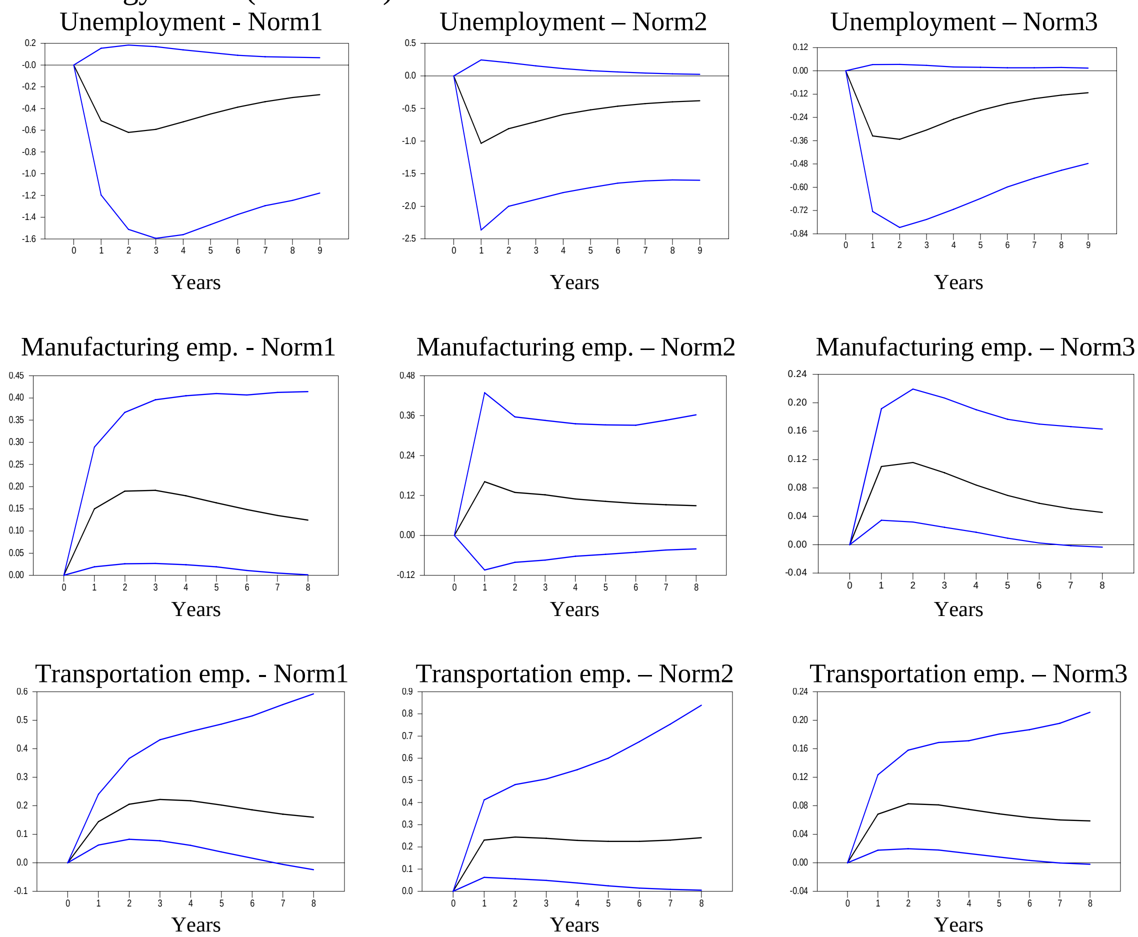


Figure 6. Employment, Hours, Unemployment and Vacancies Responses to an Aggregate Technology shock – (Bowkers case)

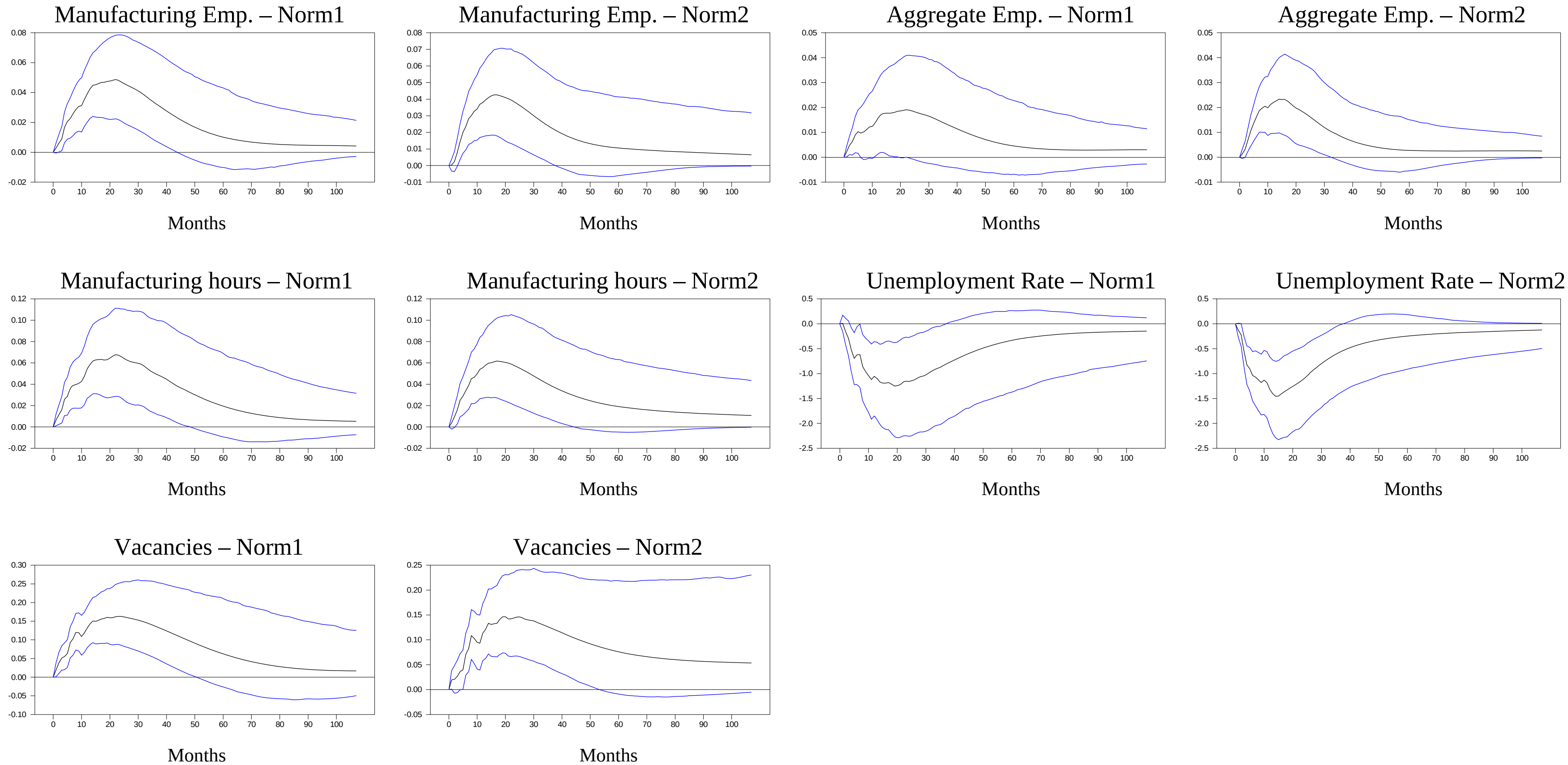


Figure 7: Labor Market Turnover Variables' responses to a positive technology shock

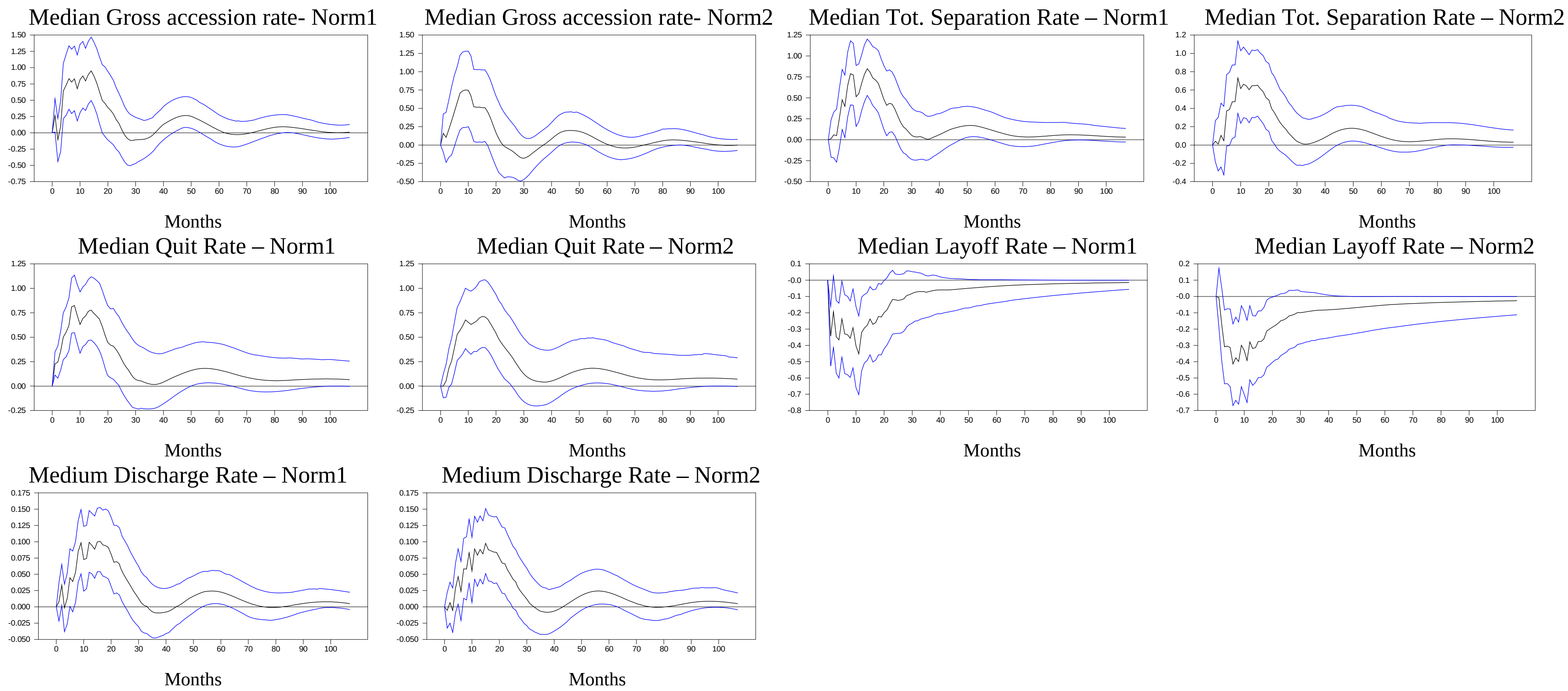
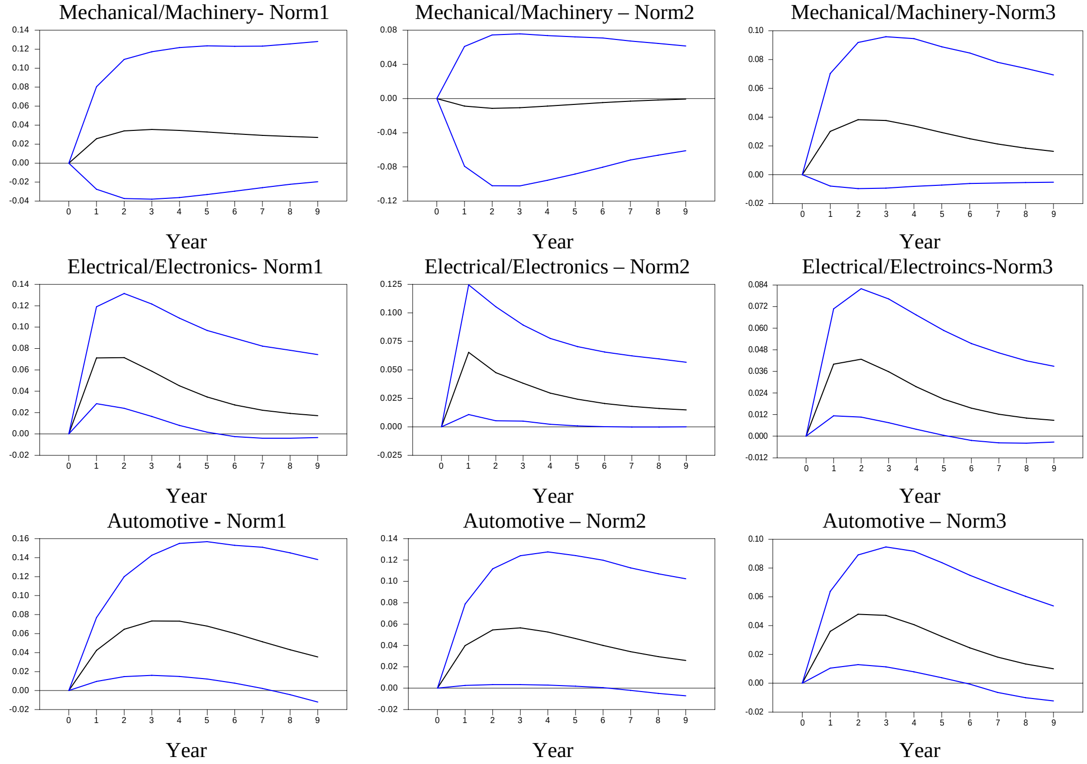


Figure 8A: Employment Responses to Disaggregated Technology shocks

Private Non-farm Employment



Aggregate Employment

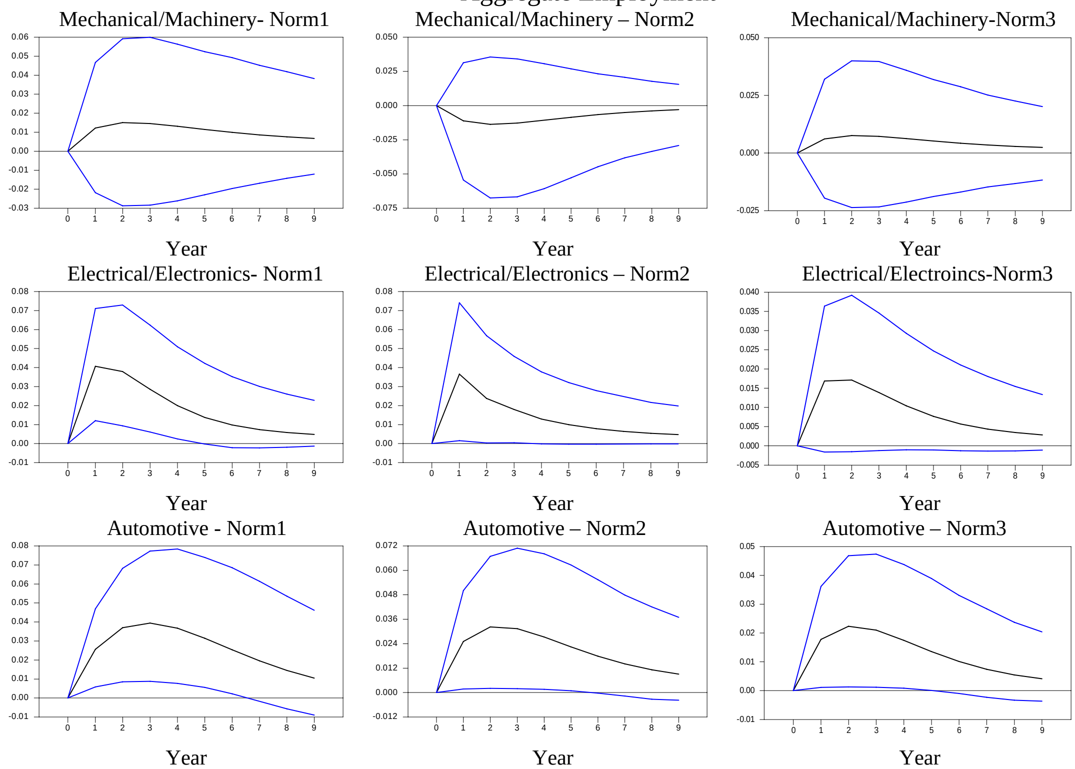
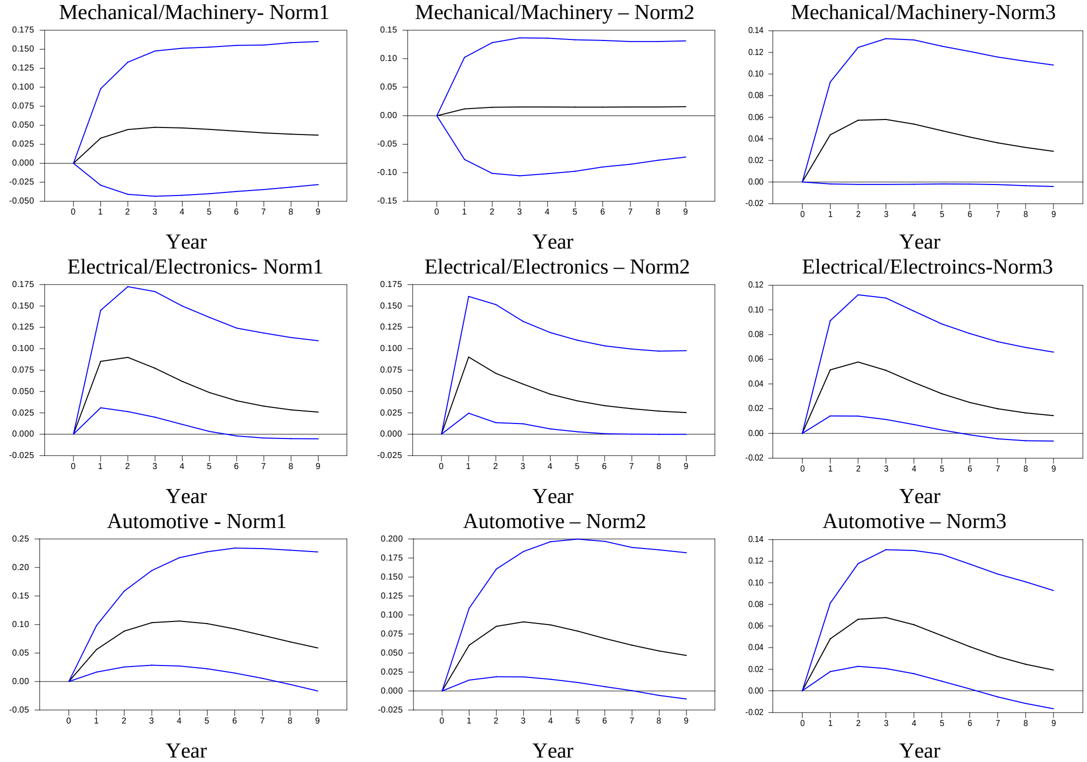
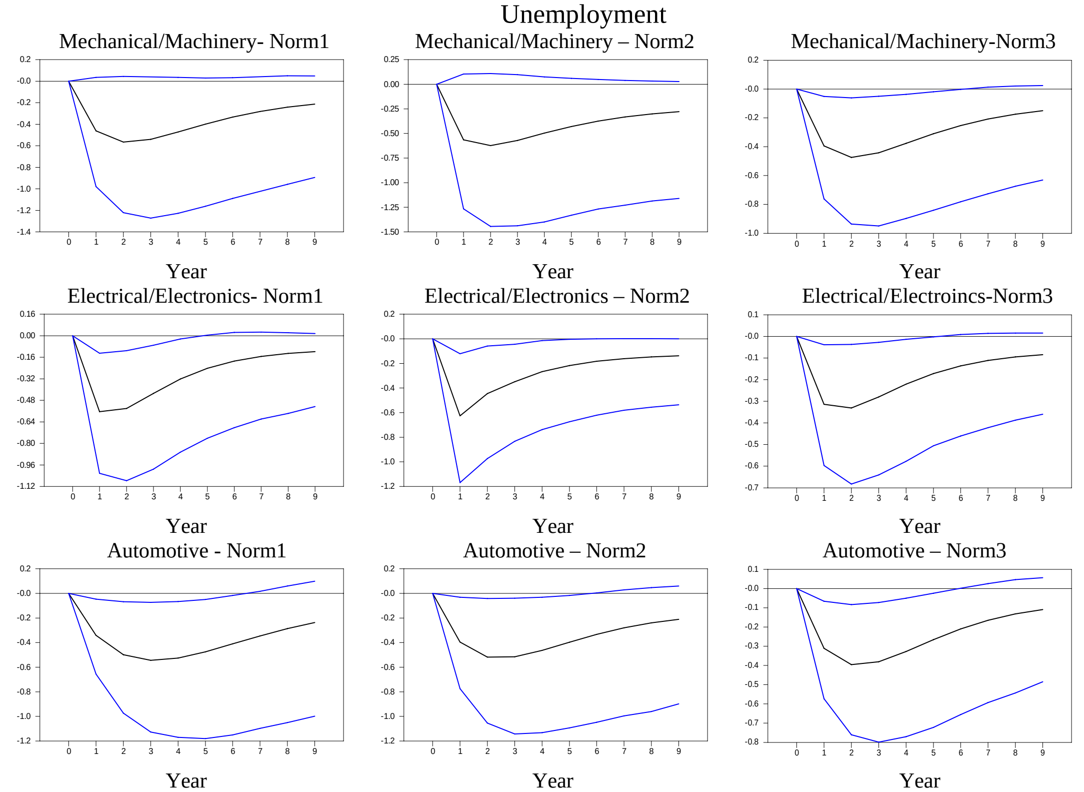


Figure 8B: Employment Responses to Disaggregated Technology shocks

Hours

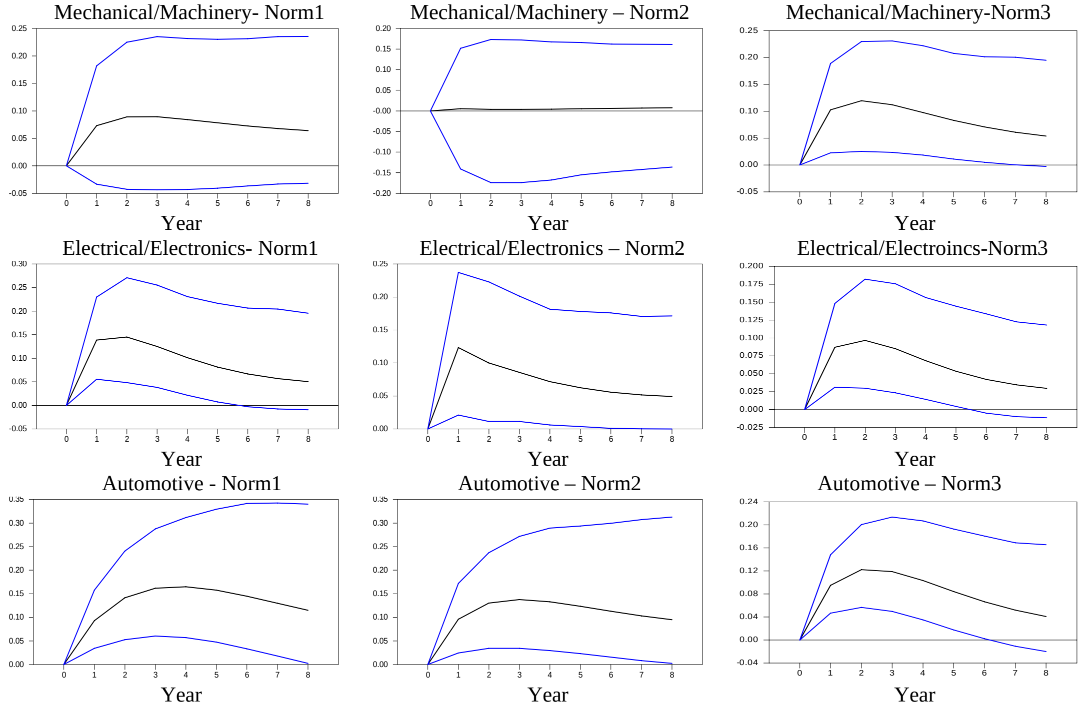


Unemployment



Figures 8C: Employment Responses to Disaggregated Technology shocks

Manufacturing Employment



Transportation employment

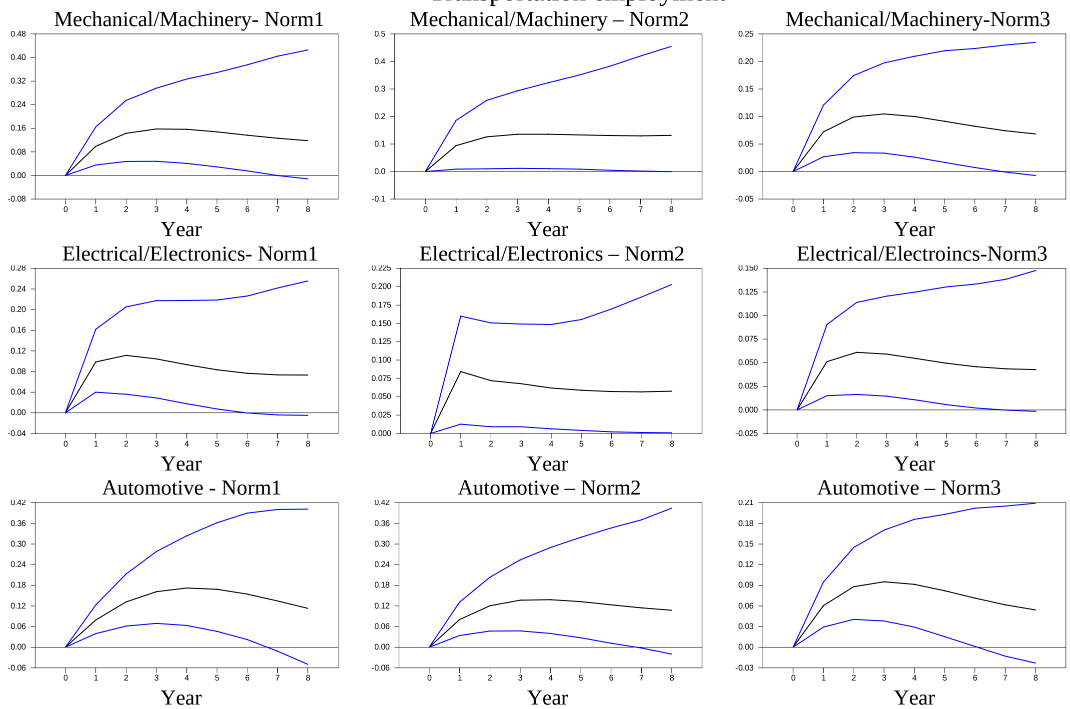


Figure 9: Sensitivity Analysis- The responses of Employment to Technology shocks