Read all about it!! What happens following a technology shock?

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Abstract:
In standard real business cycle models, a large component of the fluctuations is attributed to technology shocks. Unfortunately, empirical evidence examining the role of technology shocks is sparse, in part because they are notoriously difficult to measure. In this paper, I create new indicators of technological change based on books published in the field of technology, and use these indicators to examine what happens to the economy following a technology shock. My findings indicate that, in response to a positive technology shock, employment, total factor productivity and capital all significantly increase. (JEL E32, O3)

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1. Introduction:

For decades economists have searched for the sources of business cycle fluctuations. Early business cycle research focused on trying to predict business cycles by examining which variables lead and lag the business cycle (See e.g., Burns and Mitchell (1946)). While many of these indicators are still in use today, they do not provide much insight into the sources of fluctuations.[1]

One popular theory, embedded in standard real business cycle models, suggests that business cycles are caused by unexpected changes in the level of technology used in the economy. Although this explanation is intuitively appealing, the problem remains that technology, and technology shocks, are difficult to measure. As a result, it has been challenging to determine empirically: (1) how important technology shocks are in explaining fluctuations over the business cycle, and (2) how the economy responds to unexpected changes in technology. The answers to these questions are essential for uncovering the driving forces behind business cycles, and for determining which models are consistent with the data.

In this paper, I add to the growing literature that attempts to address these important issues. Specifically, I first create new measures of technological change based on new information from R.R. Bowker and the Library of Congress database. Next, I use these

[1] Examples include the index of consumer sentiment, the unemployment rate, and the level of business inventories.

measures in vector autoregressions to explore how the economy responds to a technology shock.

The results of my analysis suggest that a positive technology shock (an increase in the orthogonal component of the technology indicator) causes employment, total factor productivity and capital to increase (by affecting investment). The variance decompositions suggest that changes in technology have a relatively small effect on the number of hours worked at short run horizons. However, I find that technology (especially computer technology and telecommunications technology) significantly influences GDP by affecting total factor productivity and capital accumulation. The finding that computer and telecommunication technology is important in explaining fluctuations in GDP is consistent with the recent literature that finds a positive link between information and communications technologies and economic growth.[2]

The existing business cycle literature has proposed three ways to identify technology shocks. The first method attempts to identify technology shocks using long-run restrictions in a structural vector autoregression (VAR).[3] The second approach attempts to correct the Solow residual by controlling for non-technological effects such as increasing returns, imperfect competition, varying capital and labor utilization, and aggregation effects, and uses the corrected residual as the "true" measure of technology.[4] The third approach, attempts to

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[2] See e.g., Wilson (2004), and the literature on telecommunications and computer technologies affect on TFP.

[3] This method is seen in papers such as Gali (1999) Gali and Rabanal (2004), Francis and Ramey (2003), Christiano, Eichenbaum and Vigfusson (CEV (2002, 2004)), Altig, Christiano, Eichenbaum and Linde (ACEL (2003)) and Fisher (2003).

[4] This method is developed by Basu, Fernald and Kimball (BFK (2004)).

measure changes in technology in a more direct way using information on research and development expenditures (R&D) and patent activities.[5] While each of these methodologies has strengths and weaknesses,[6] the approach I use in this paper is most closely related to Shea's (1998) work using direct measures of technological change. However, I develop and utilize new measures of technological change that overcome some of the shortcomings associated with the traditional measures based on patents and R&D expenditures.

The use of patents and R&D as direct indicators of technological progress has a long and distinguished history (see Griliches' (1990) survey paper). This research leads Shea (1998) to explore the impact of technology shocks on the economy using these direct measures in a VAR framework. In his paper, Shea (1998) argues that using direct measures of technological change (such as R&D and patents) has two main benefits. First, unlike Gali's (1998) method, the results do not rely on the assumption that only technology shocks affect productivity in the long-run (an assumption that would be violated if there is endogenous growth for example). Second, the indicators are more directly linked to technological changes than the corrected residual method used by BFK (2004), especially if the correction is incomplete.

While Shea's (1998) methodology is appealing, his results using the standard patent and R&D measures findings were mixed. For example, it appeared that changes in

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[5] Shea (1998) uses this information in a VAR to help identify technology shocks.

[6] See Christiano, Eichenbaum and Vigfusson (2004) and Gali and Rabanal (2004) for discussions on the strengths and weaknesses associated with assuming that only technology shocks affect labor productivity in the long run. See Shea (1998) and Christiano, Eichenbaum and Vigfusson (2004) for a description of the potential shortcomings of the BFK measure of technology, and see Gali (1998) and Jaffe (1998) for a discussion of the problems using patents and R&D expenditures to measure changes in technology.

technology (as measured by his patent indicators) had no statistically significant impact on inputs or total factor productivity (TFP) for many of the sectors examined. For others, he found that technology shocks decreased TFP and increased inputs in the short run.

Although the weak relationship between TFP and technological change Shea (1998) finds using the traditional measures may be troubling on the surface, they may not be surprising. According to the business cycle theory, a technology shock occurs when output is affected, not when the R&D takes place or when an innovation is patented. Therefore, Shea's (1998) findings may be attributable to the long time lags between when an idea developed, patented and when it may be used, and the fact that less than 20% of patents lead to commercialize products.[7]

My approach for exploring the impact of technology shocks is closely related to the one used by Shea (1998). However, instead of using data on patents (or R&D), I create a new measure of technological change that circumvents some of the problems associated with the traditional patent and R&D measures. My new indicators are based on previously unstudied information on book titles in the fields of technology used in the U.S. economy and are compiled using information from three sources: R.R. Bowker Company, the Library of Congress and Autographics/Thompson Dialog Corporation. Historically, Bowker has published many of the book lists regularly used by libraries to keep track of the new book titles available in the U.S. market. The files obtained from the Library of Congress' MARC21 records database (1968-1997) and the Library of Congress' REMARC database, accessible through Dialog/Autographics, provide information on most new books

[7] See BFK (2004) and Geisler (2000).

copyrighted within the United States from 1955-1997 in a format which can be used to create the measures of interest.[8]

There are two major benefits associated with utilizing my new publication-based indicators of technological change. First, they are more closely related to the type of technology shocks modeled in the business cycle literature. Second, since they do not incorporate the same type of time lags as patents and R&D measures, they provide stronger results.[9]

The rationale for using this new books indicator is that, like patents, the introduction of new titles (excluding new editions) in the field of technology should capture technological progress. Moreover, new books on technology (e.g., manuals) are likely to be written when the idea or product is first being utilized or is in the process of being implemented, since books are costly to produce and publishers want to recoup these costs. Therefore, the lag between changes in technology captured by my indicator and economic activity should be much smaller than the corresponding lag when technological change is measured using

[8] Besides being the largest library in the United States, the Library of Congress is a copyright depository for works published in the U.S. For example, the Copyright Act of 1978 established a mandatory deposit requirement for works produced inside the U.S. boundaries within 3 months of publication in the United States.

[9] Fisher (2003) has argued that investment specific technology shocks are responsible for the majority of the fluctuations seen over the business cycle. Since my indicators are closely linked to the type of machinery and capital that is used in the economy, this may also provide an explanation as to why my indicators produce stronger results.

research and development expenditures or patent indicators.[10,11] Indeed, the results presented in this paper suggest that, while changes in patents require a 4 year lag to affect the economy, my technology indicator appears to lead changes in TFP and GDP by approximately one year.

In addition to exploring the properties of these indicators, I use them to explore the response of the economy to a technology shock using vector autoregressions. Like Fisher (2003), CEV (2002, 2004) and ACEL (2003) my findings support the predictions of the standard real business cycle model. Specifically, they suggest that in response to a positive technology shock, real GDP, employment, total factor productivity and capital all significantly increase after one year with the peak impact occurring after 3-4 years following the shock.[12] However, my finding that only a modest amount of the short run variation in

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[10] See Alexopoulos (2004) for some evidence about the lags between product discovery and introduction to market.

[11] As a result, this new measure should be more in line with technology shocks assumed in business cycle models, which occur at the time at which output is affected – not at the time that the innovation process is patented.

[12] These findings are in partial contrast to the findings presented in Gali (1999), Francis and Ramey (2003) and Basu, Fernald and Kimball (2004). Their findings suggest a positive technology shock will increase GDP but may actually decrease the amounts of labor and capital inputs used in the first year. However, CEV (2002), ACEL (2003), and Fisher (2003) have argued that: (1) Gali's (1999) and Francis and Ramey's (2003) results are driven by their assumption that hours worked is not a stationary series, and (2) if one assumes hours worked is stationary, their methodology predicts that positive technology shocks are expansionary. Moreover, CEV (2004) argues that measurement error may explain the results found by BFK (2004).

employment can be attributed to technology shocks is generally consistent with the findings in the other papers.[13]

The remainder of the paper is organized as follows. In section 2, I discuss the relationship between TFP and direct measures of technological change, describe the data used to create the indicators, and explore how my research relates to the literature on patents and research and development. In section 3, I present results on the relationship between GDP, TFP and inputs and the book indicators. Single equation estimates of the contemporaneous relationship between both GDP and TFP and the indicators are reported along with the results of vector autoregressions (VARs) when the book indicators are used to identify changes in technology. These results are then compared to those obtained when new patents applications and research and development expenditures are used as indicators of technological change. In section 4, I conclude and offer suggests for future research.

Section 2.

Direct measures of technological change

To date there are few direct measures of technological change used in economics. The most common of these measures are based on research and development expenditures, patent statistics, and more recently, patent citation statistics.[14,15] As Griliches pointed out in

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[13] Fisher's (2003) findings are an exception. He finds that investment specific shocks have a very large impact on labor.

[14] A far less common measure has been the number of trademarks issued in the U.S. (see Yorukoglu (2000)).

his 1990 survey paper, patent (and R&D) statistics have fascinated economists for a long time. The reason is simple – these statistics are inherently linked to changes in knowledge and may help us obtain answers to important questions such as reasons for changes in economic growth and productivity.

Figure 1 outlines the relationship between R&D, patents, technology and economic activity suggested by Griliches (1990). In this case R&D expenditures are considered inputs into the production of technology/knowledge, while patents are a measure of the output of the development process. Therefore, he argues, patents should be a noisy measure of technological change.

While patent statistics contain a large amount of important information, they are still subject to a number of short-comings - especially for the purpose of studying the effects of technological change in the short run (i.e., at business cycle frequencies). First, there are usually long, and variable, lags between the time that a product or idea is patented and the time that the product or process is actually put into use.[16] In extreme cases, a product idea is patented but never put into use.[17] Second, patent fluctuations in the U.S. may partially be due to changes in patent law and/or changes in the resources of the U.S. patent office (See Griliches (1990)). For these reasons, studies using patent statistics to measure changes in

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[15] See Griliches' (1990) survey article and Jaffe and Trajtenberg (2002) for good overviews of the patent literature.

[16] For example, while the first photocopier was developed and patented in the 1930s, the first photocopier machine was not commercially available until 1950.

[17] Geisler (2000) reports that a survey of 23 large firms indicated that over 80% of patented items never resulted in commercial products.

kind of the technology relevant for business cycle models may conclude that technology shocks do not significantly affect TFP or inputs even if that this not the case.[18]

Given the potential problems with patent data, we would prefer an indicator of technological change that is: (1) related to information available on research and development expenditures, and (2) is closely related to technology that is *actually adopted* in the economy. I argue that the new indicators created from information on new titles published in the fields of technology and computer science satisfy these criteria. The reason is simple. Indicators based on the publication of new books in the field of technology should reflect technological progress. Moreover, new books on technology (e.g., manuals) are written when the idea or product is first being utilized (or is in the process of being implemented) since: (1) books are costly to produce, and (2) publishers want introduce the books as early as possible to maximize the return on each new title.[19,20] As a result, the new

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[18] The problems related to using patents to measure the changes in the type of technology relevant for business cycle models were raised by Basu and others during the discussion of Shea's (1998) paper at the 1998 NBER Macroeconomics Annual Meeting, (See pp. 320-1 in the 1998 Macroeconomics Annual).

[19] Although one might initially worry that there is a significant time lag associated with producing new books, my discussions with publishers indicate that the publication lags for technology books is relatively short. Specifically, they reported that they can release a book on a major technological development within 3 months (with a 6 month average). This occurs since technology is a rapidly changing field and publishers recognize that any delay in releasing new titles about new technologies can result in the company failing to realize maximum revenues if their competitors are able to release a similar book faster.

[20] In addition to the books produced by major publishers, companies like IBM, Microsoft and Goodyear also release manuals when they introduce new technologies.

technology titles should reflect new technologies introduced in the economy. Furthermore, the lag between the changes in technology captured by my book measures and changes in economic activity should be much smaller than lags associated with the more traditional indicators.

Creating the New Measure:

To create the new indicators, I require information on the type of books available each year, information on the book edition, and data on which country created the books. Specifically, I want to focus on the number of new titles in different fields of technology each year, excluding books written on the history of a particular technology, to identify new technologies available in the economy.

This type of information can be obtained from two sources – book publishers and libraries. My indicators are created using information from: R.R. Bowker company, the Library of Congress and Autographics/Thompson Dialog Corporation.

R.R. Bowker publishes many of the book catalogues used by American libraries to keep track of new book titles by major subject fields that are available within the U.S. market. Their measure of American Book Production is reported on a yearly basis in Bowker's Annual Yearbook.[21]

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[21] Alexopoulos (2006a) provides additional information on how the number of new titles in different categories outlined in Bowker's is related to economic growth in the United States.

From 1955-1997 Bowker reported annual estimates of how many new titles were available in the American market in different subject groups (e.g., Technology, Science, History, Home economics, etc) during the year. In the early years, their estimates were based on information collected using surveys of the major book publishers in the U.S. Later they were based on information obtained from the Library of Congress's Cataloguing in Publication Program (CIP).[22] The technology indicators created from this data source are graphed in Figure 2.

While Bowker's estimates represent a general pattern of books in technology marketed by major book sellers in the U.S., the statistics suffer from two drawbacks. First, they do not cover all books produced and sold in the U.S. (e.g., manuals printed by companies like Microsoft or Ford may be missed). Second, their measure of technology does not include books on computer technology. Instead, books on computer technology are grouped together with dictionaries and encyclopedias.[23] To resolve this problem I create indicators for computer technology and telecommunications technologies from records in the Library of Congress database.[24]

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[22] The Cataloguing in Publication Program collects information from major publishers about books published in English for the American market that are likely to be mass marketed and carried by a large number of libraries.

[23] This occurred because the Bowker's categories are based on the Dewey Decimal Book Classification, which classifies computer books, along with dictionaries, encyclopedias, bibliographies and reference books, as general knowledge.

[24] Even though the Library of Congress database is more complete, it is still useful to examine the statistics from Bowker's since the later primarily focuses on titles that are available from the major publishers in the U.S. and uses a different classification system.

The Library of Congress distributes database files in MARC21 format (See Figure 3 for a sample of a Marc record and the corresponding database file). These files are used by the Library of Congress to run their online book search program, and are distributed to other libraries to be used for cataloguing purposes. The Library of Congress' collection contains information on a larger number of publications than R.R. Bowker's data since the Library is the copyright depository for the U.S., and the largest library in the U.S.[25] As a result, the Library's MARC21 records database (1968-1997) and their REMARC database, accessible through Dialog/Autographics, provide information on new books copyrighted within the United States from 1955-1997 in many subject fields, as well as information on books imported from other countries.

The MARC21 records are in machine readable form, and contain information that identifies the type of book (e.g., new title or edition), the country of publication, the language of publication, the Library of Congress' Classification Code, and a list of major subjects covered in the book. The information in the first three fields allows me to identify books in English, published in the US, that are new titles. The Library of Congress Classification Code is what librarians use to group books on similar topics together (e.g., science books, technology books, economics books, etc).[26,27] For the purpose of this investigation I will be

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[25] The Library of Congress' collections include more than 29 million books and other printed materials.

[26] See Appendix A for a listing of the major groupings and sub-groupings in T and Q.

[27] The Library of Congress Classification is different than the Dewey Decimal System Classification used to compile the Bowker's series. Therefore, the aggregate technology series based on the Library

primarily looking at books listed in the main subgroup T (which identifies the book as being in the field of Technology)[28], the subgroup of T that identifies traditional telecommunications technologies (TK5101-6720) and QA75-76 (which identifies books in Computer software and hardware). The information contained in the subject fields in the MARC21 record, along with the title field, allow me to remove books from these groups that list history as a major topic.[29] Figure 4 presents the aggregate indicators on technology and computer science based on the information from the Library of Congress' records. Here I report two different series for computers. The series entitle COMP1 contains the number of new titles on computer software and hardware catalogued by the Library of Congress under QA75-76, while series COMP2 contains the titles in COMP1 and new titles on computer networks that are catalogued under the T section.

The relationship between books, patents and R&D

Books on technology and computers are published when the new technology has been commercialized and is in the process of being implemented. As a result, we might expect

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of Congress data will differ from the Bowker's series in more than just the type of new books considered.

[28] A number of the books in Subgroups TT (Handicrafts) and TX (Home Economics) are excluded to focus on new technologies in use in the market economy.

[29] Books with history in the title or indicated as a major subject are removed to exclude books that have no real link to current technology (e.g., a book on the Life of Alexander Graham Bell published now will not tell us much about the current state of technology in the communications industry).

that R&D expenditures should be leading indicators of the number of new technology titles. The linkage between books and R&D can be described by Figure 5, where once again R&D can be viewed as an input. In addition to R&D leading to new technology, increases in scientific knowledge, or patents, may also lead to more books in the field of technology if the different measures are indeed capturing the same technological change.

To investigate the relationships between these different measures of innovative activity, I explore whether patents, science books[30], or R&D expenditures Granger-cause the number of new titles in technology.[31] The numbers reported in Table 1 provides some support for the existence of a relationship between R&D expenditures, science books and technology books.[32]

When new titles in Science are used as a measure of changes in scientific knowledge and R&D intensity is proxied by R&D expenditures, we find some evidence that both Science books and R&D expenditures Granger-cause new books on technology and computer science. However, there is little evidence that patents Granger-cause books on technology.

[30] The Science indicator is based on Bowker's measure of new Science titles. They include books published by major publishers in the United States in the field of Science (excluding Medicine).

[31] The data on the number of patent applications by year can be obtained from the U.S. Patent Office and statistics on R&D expenditures are available from the National Science Foundation. The expenditures were converted to real R&D expenditures using the GDP deflator.

[32]The results are similar if the stock of R&D (as defined in papers such as Lach (1995)) is used instead of the flow.

There is also some evidence of a feedback between technology and science since new technology titles appear to Granger-cause patents, R&D spending and new titles in Science. Specifically, the results suggest that computer titles Granger-cause science titles and R&D expenditures with a two-period lag. In addition, the LOC new technology titles Granger-cause new science titles, patents and R&D expenditures.[33]

These results help strengthen the argument that the new book measure of technological change is an output of innovative activity. However, to better understand the properties of the new measures, it is still necessary to examine the relationship between technological diffusion and the publication of new titles.

Just a Measure of Diffusion?

Even though it appears that the new indicators are correlated with the introduction of new technologies, it remains to determine if the new indicators are only tracking technological diffusion or whether the date of the first book(s) on a subject appears to coincide with what we know about the introduction of new products to the market. Below I present a number of reasons to believe that diffusion alone does not explain the patterns seen in the book indicators.

First, companies introducing new technology products will release new instruction manuals at the time that the product is comes to market (not afterwards)[34], and book

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[33] Interestingly, the results indicate that an increase in the number of new titles published in the field of technology decreases the number of patents.

[34] For example, the MARC21 record displayed in Figure 3 is the manual that was shipped with C++ when it was first introduced to the market.

publishers are likely to introduce books on the subject shortly afterward, given their incentive to maximize profits. This suggests that the majority of manuals/new book titles precedes the majority of the technological diffusion. Although it is impossible to verify this for all technological advancements, some case studies can be examined to see if this pattern emerges. Consider, for example, the timeline and graph for Computer hardware, shown in Figure 6A. The book measure indicates that the period 1980-84 was a period of rapid technological change in computers. In fact, this period corresponds to the first wave of personal computers (IBM PC, the first IBM clones, the first Macintosh computer, and the first laptop) introduced to the market and large changes in the power of computer processors.[35,36]

Second, the data on the share of computers in durable expenditures does not have the same pattern as the computer indicators based on publications (See Figure 6B). Specifically, in contrast to the book indicator, there is no peak in the share of expenditures in 1984, and no decline between 1985 and 1990. Instead, the data on expenditures suggest that computer

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[35] Alexopoulos (2004) also provides an example based on books on penicillin. Although the healing properties of penicillin were discovered in the 1920s, books on penicillin did not appear in the Library of Congress until approximately 1940 when the drug companies published manuals for doctors on how to treat patients with penicillin. The reason for the long lag (between discovery and publication) again demonstrates the usefulness of the new measure in certain fields. The history of penicillin confirms that it was impossible to produce commercial grade penicillin until the early 1940s because additional technology needed to be developed.

[36] A similar patter for the 1980s appears if we graph new titles in both hardware and software. However, when software is included, there is a larger increase in books seen in the 1990s which corresponds to the introduction of the internet.

technology that began diffusing in the late 1970s had not yet stopped. Moreover, the data on the share of computer and periphery equipment in the total net stock of non residential capital reported in Oliner and Sichel (1994), also peaks much later than 1984.

Third, the data on the relative prices of computers and software, reported in papers like Jorgenson (2001), demonstrate that the decline of prices in the early 1980s was no more phenomenal than the price decreases witnessed in the preceding decade (See e.g., Figure 6A).[37] This suggests that consumer demand for computers would not have accelerated during the early 1980s simply due to rapidly decreasing product prices.

In addition to this aggregate evidence, new book indicators at a more disaggregate level can be used, along with information on sales of more specific technologies, to determine the relationship between the diffusion of the technology and the corresponding book indicator, when the appropriate data are available. Although it is not possible to distinguish the difference between diffusion and introduction for a product in my dataset if it is only on the market for a year, it is possible to examine the relationship for products with a longer lifespan. The graphs presented in Figures 6C and 6D are examples of computer technologies that have books published about them, as well as available data on the number of units sold. Figure 6E presents a similar case study using estimates of the net increase in wireless subscribers and the number of new titles published on cellular telephone systems.

Figure 6C presents data for one of the most successful computers ever marketed – the Commodore 64. It was first introduced in 1982, and during its lifetime it is estimated that between 17 and 30 million machines were sold. The data presented in the graph depict the

[37] Figure 6A graphs Jorgenson’s Hardware Price Index for the period 1967-1997. This data is available at http://post.economics.harvard.edu/faculty/jorgenson/papers/AEADAT200305182005.pdf

number of new titles published in the US on the subject Commodore 64 (Computer), and an estimate of the number of units sold between 1982 and 1993.[38] The figure clearly illustrates that the number of new titles peaks much earlier than yearly sales. Even if we assume some people retired their computers after only a couple of years, clearly the pattern of book publications does not match the pattern of technological diffusion. The number of new titles peaked well before Commodore International stopped producing and marketing this computer.

The graph in Figure 6D shows a similar pattern for a very popular software product – Microsoft Windows 3.1. Windows 3.1, introduced in April 1992, was one of the highest selling software programs during the years that it was in production. Available statistics suggest that more than 100 million copies of this product had been sold by the time that Windows 95 was release in 1995, and more than 130 million licensed copies were in use by the time that Windows 3.1 was completely taken off the market.[39] Again, the graph confirms that the number of new titles peaks well in advance of the sales. In fact, the number of new titles hits its high during the first year the product was available. Again, the production of new book titles appears to lead the diffusion of the technology in the computer industry.

Figure 6E documents a similar pattern in the telecommunications industry. One of the big developments in this industry during the last 20 years has been the introduction of the cellular phone. The first commercial cellular system was introduced in Chicago in October

[38] The data is available from Jermey Reimer's webpage http://www.pegasus3d.com/total_share.html, and is reported in Reimer (2005).

[39] Estimates on the number of Window's programs licensed were obtained from Gartner Dataquest's historical Press Releases.

1983, with the second system introduced in December 1993 in the Baltimore-Washington Area. The graph depicts the net increase in wireless subscribers over the time period 1984-1997, and the number of new titles on cellular telephone systems.[40] The numbers until 1992 are based on the number of cellular users, while the estimates available for subscribers after this date do not distinguish between wireless subscriptions for cellular users and subscriptions for personal communication systems (e.g., text messengers, etc) and ESMR (Enhanced specialized mobile radio). This change in the statistics coincides with major changes in cellular technology in 1992 and 1993. For example, the first commercial text message was sent in 1992 and in 1993 Bell Labs developed the digital Signal Processor for use in handsets. Indeed, a number of the new titles seen after this date contain additional subject classifications (besides cellular telephone systems) that reflect the changes in wireless technologies available to cellular phone users. Once again, it appears that the number of new titles in cellular telephone systems leads the diffusion of this technology.[41] More generally, the case studies, together with the aggregate evidence, support the proposition that the new book indicators measures technological change, not technological diffusion.

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[40] Books on Cellular Handsets are a subgroup of this category. The Statistics are available from CTIA – the Wireless Association's website www.ctia.org.

[41] The conclusion is similar if I use changes in the number of cell sites to measure the diffusion of the technology. For example, in 1984 there were only 346 cell sites, with the number steadily increasing to over 51,000 by the end of 1997.

Section 3:

Direct measures of technology and changes in GDP

While I have presented some evidence that the books indicators are related to changes in the level of technology available in the economy, it remains to be seen if there are relationships between the book indicators and changes in GDP. Figure 7 provides an example of the relationship between the new indicators and changes in real GDP. The figure depicts changes in the technological indicator obtained from the Bowker's data and changes in real GDP. The graph indicates that significant changes in the number of new titles precede almost all recessions and expansions.[42] There is, in other words, reason to believe the new indicators provide a compelling measure of technological change.

A more formal analysis confirms that the new technology indicators affect real GDP with a lag. Although there is a contemporaneous relationship between the indicators and GDP, Table 2 confirms that, once the lagged variables are accounted for, the current level of the new indicators do not appear to affect GDP.

Using a two variable VAR, where $Y_t = \alpha + \gamma t + \rho Y_{t-1} + \varepsilon_t$ and $Y_t = [\ln(GDP_t), \ln(X_t)]'$, I investigate whether the technology shocks identified by the indicators have a significant impact on GDP.[43] Similar to Shea (1998), I assume that the technology shock only affects

[42] In fact, there are also changes in the number of new books prior to the growth slowdowns discussed by Zarnowitz (1992).

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

GDP with a lag.[44] Figure 8 displays the impulse responses of GDP to a technology shock for each of the indicators used along with 1.65 Monte Carlo standard error bands. These figures illustrate that GDP significantly rises in response to a positive technology shock with the peak response occurring after 2-4 years.[45]

While the relationship between Patents and GDP is weak, the results in Table 3 indicate that the new book-based technology indicators Granger-cause GDP. However, the reverse is not true. The tests indicate that GDP does not Granger-cause the new technology indicators.

Table 4 displays the variance decomposition implied by the VARs at the 3, 6 and 9 year horizons. Three patterns emerge in this table. First, the percent of variation in ln(GDP) due to technology at a 3 year horizon is approximately 10-20%, with this effect doubling over the next 3 years. Second, the computer and telecommunications indicators explain more of the variance than the general technology indicators.[46] Third, the new indicators are better

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[44] To determine if the ordering had a significant impact on my results, I also ran VARs with the Technology indicator entering before ln(GDP). I found little evidence to suggest that the results from the bi-variate VAR were sensitive to the ordering of the variables.

[45] As Alexopoulos (2006b) demonstrates, these results are generally unaffected by the inclusion of other shocks such as monetary policy shocks, oil shocks, and fiscal policy shocks.

[46] The Science indicator likely performs well in the medium to long-run because of its affect on Technology.

able to explain the variation in GDP than the more traditional indicators (i.e., patents and R&D expenditures).[47]

Just Trends in the Publishing Industry?

Since there may be some concern that the changes in the number of technology books simply capture trends in the publishing industry as a whole, I explore how the impact of changes in the number of new technology books differs from the impact of changes in the number of new titles in history. While both of these series should be influenced by changes in the publishing industry, new titles in history should be unrelated to changes in technology in the economy. As a result, if changes in the number of history titles are not related GDP or TFP, this will help bolster the case that changes in technology titles are genuinely related to changes in the technology used in the economy.[48] Figures 7 and 8, along with the results reported in Tables 2, 3, and 5 suggests that an indicator based only on the number of new history books does not have the same relationship with changes in GDP or the TFP measures.[49] Therefore, it does not appear that the relationship between GDP and the new

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[47] Similar results emerge for the computer and telecommunications indicators when the first difference of ln(GDP) is used instead of the level.

[48] It is also the case that ln(history new titles) and lags of this variable have no significant explanatory power for ln(patents) or ln(R&D expenditures) in regressions that contains the new technology indicator, GDP and lagged values of either patents or R&D.

[49] Similar results are obtained using new titles in other fields (e.g., new titles in music, drama and poetry) that: (1) are unlikely to be correlated with changes in technology that could have an impact on

technology indicators can be simply explained by changes in the publishing industry as a whole.

Direct measures of technology and the components of GDP

While the results about the relationship between the new indicators and GDP may be informative, it is important to explore how technology shocks affect TFP, capital and labor. The methodology used for this analysis is similar to the one used by Shea (1998). However, I use the new indicators of technological change in my regressions and consider multiple measures of total factor productivity growth.

Measures of Total Factor Productivity: There are many ways that economists measure total factor productivity. For the purpose of my analysis, I use two of the most common measures.[50] The first measure I use is the Tornqvist Measure of TFP:

$$\text{Tornqvist Measure}_t = \Delta\ln(Y_t) - 0.5(\alpha_t + \alpha_{t-1})\Delta\ln(K_t) - (1-0.5(\alpha_t + \alpha_{t-1}))\Delta\ln L_t$$

where, K_t is measured using time period t data on the fixed reproducible tangible assets for the United States, Y_t is real GDP in time t and L_t is the corresponding number of employment

---

economic activity, and (2) would be affected by changes in the publishing industry. (See Alexopoulos (2006a))

[50] In this version of the paper, I do not report the results for TFP based on the simple Solow residual, i.e., $\ln(TFP_t) = \ln(Y_t) - \alpha\ln(K_t) - (1-\alpha)\ln L_t$ where α=1/3, since the results are virtually identical to those of the Tornqvist Measure.

hours. This measure assumes that firms are perfectly competitive. However, the elasticity of output with respect to capital and labor are allowed to vary over time.[51]

The second measure is the state of the art cleansed Solow residual created by Basu, Fernald and Kimball (2004).[52] Their purified measure of the Solow residual takes the aggregation issue seriously and attempts to correct for changes in utilization, imperfect competition and non-constant returns to scale.

Table 5 examines the contemporaneous relationship between changes in the TFP measures and changes in the book indicators. Similar to the findings for GDP, the results demonstrate that the technology captured by the indicators appear to affect TFP with a lag. Furthermore, the evidence suggests that the measures of TFP are most influenced by the computer and telecommunications technologies.

The impulse responses of TFP to the technology shocks are depicted in Figures 9 and 10. They indicate that positive shocks to technology – as measured by increases in the orthogonal component of my technology indicator – increase TFP in the short run. However, there are significant differences in the size of the responses across the measures of TFP. Specifically, the responses for the cleansed Solow residual (Measure 2) are only significant for the computer and telecommunications technologies, while the responses of the Tornqvist Measure of TFP to the technology shocks are virtually all significant at the 10% level.

---

[51] The data for L,K, and Y are obtained from the National Accounts Data obtained from the Bureau of Economic Analysis. In addition, I use their data on labor's share of income each year to compute α_t

[52] The BFK series here is their cleansed residual for the Non-Agriculture, Non-Mining Business Economy. As a result, their residuals are not directly comparable to the Tornqvist measure which is based on statistics for the entire economy. In addition, their data series ends in 1996.

Table 3 reports the Granger-causation results for the bi-variate TFP VARs and Table 4 displays the variance decompositions for the TFP VARs alongside those from the bi-variate GDP VARs. Again, it appears that: (1) the new indicators Granger-cause TFP for many of the cases, (2) there is little evidence that TFP Granger-causes the indicators, and (3) computer and telecommunications technologies appear to explain a significant portion of TFP variation, regardless of the measure used.

Next, I expand the number of variables in the VAR to include changes in Capital, labor and TFP. Specifically, I assume that $Y_t = \alpha+\gamma t+\rho Y_{t-1} +\varepsilon_t$ where $Y_t = [\Delta\ln(K_t), \ln(N_t), \ln(TFP_t), \ln(X_t)]'$ or $Y_t = [\Delta\ln(K_t), \Delta\ln(N_t), \ln(TFP_t), \ln(X_t)]'$.[53] Again, I follow the convention in Shea (1998) and place the technology measure last in the ordering to reflect the assumption that shocks to this variable only affect TFP, hours and the change in capital with a lag. Since the impulse response functions for these two cases are similar, I only report the results where $Y_t = [\Delta\ln(K_t), \ln(N_t), \ln(TFP_t), \ln(X_t)]'$ for Measure 1, and $Y_t = [\Delta\ln(K_t), \Delta\ln(N_t), \ln(TFP_t), \ln(X_t)]'$ for Measure 2.[54]

[53] Although the results are similar, when $Y_t = [\Delta\ln(K_t), \ln(N_t), \ln(TFP_t), \ln(X_t)]'$ for Measure 2 the responses tend to become significant with a slightly longer lag (i.e., 1-2 periods). In the case of Measure 1, the results for telecommunications become stronger, while the results for TECH and TECH2 become weaker when $Y_t = [\Delta\ln(K_t), \Delta\ln(N_t), \ln(TFP_t), \ln(X_t)]'$. However, the results for Comp and Comp2 are found to be almost identical to those reported for Measure 2 in Table 9. The results for these other cases are available from the author upon request.

[54] Unlike papers like, Christiano, Eichenbaum and Vigfusson (2002) and Gali (1999), my results do not appear to depend on whether $\ln(N)$ or $\Delta\ln(N)$ is used in the VAR.

Tables 6 and 7 report the Granger-causality tests for the VARs using the different measures of TFP. These results show that the new technology measures tend to Granger-cause TFP and changes in capital – especially when the computer and telecommunications indicators are used. However, only the telecommunications indicator appears to consistently Granger-cause labor at the 5% level. This suggests that GDP is affected primarily through the technologies' affects on TFP and capital accumulation. In addition, the tables show that labor, and TFP Granger-cause changes in the telecommunications and Bowker's overall technology indicators when the first TFP measures is used in the regression, although this relationship vanishes when the corrected Solow residual is used (i.e., TFP measure 2).

Tables 8 and 9 report the percent of variation due to technology in the four variable VARs using the different TFP measures. These tables illustrate again indicate that the computer indicators and the telecommunications indicators appear to explain the most variation in TFP, employment and capital.[55]

Figures 11 and 12 illustrate the impulse response functions for the new technology indicators and the different measures of TFP. In general they show that a positive technology shock increases TFP and capital one period after the shock with a peak response usually occurring two periods after the shock. The TFP and capital responses are significant for approximately 5-7 years following a shock to computer technology, and 2-3 years following

[55] While patent appear to do a relatively good job at explaining variation in labor and TFP, similar to Shea (1998) I find little evidence that patents Granger-cause TFP or changes in capital and only weak evidence (a p-vale of approximately 0.1) that patents Granger-cause labor. Moreover, the corresponding impulse response functions show that a shock to patents had no significant impact on TFP, labor or capital at any horizon.

a shock to telecommunications technology. The effects on labor are somewhat weaker and depend on the type of technology considered and the measure of TFP used.

Conclusion:

The question of what happens following a technology shock is important. The answer helps us determine the extent to which technology shocks are a source of business cycle fluctuations. It also permits us to determine which competing models of economic fluctuations (e.g., sticky price models vs. standard real business cycle models) are most consistent with the data.

In this paper, I add to the literature in two ways. First, I create a new measure of technological change using previously unstudied information on new book titles in the field of technology from R.R. Bowker and the Library of Congress. Second, I use these new measures in a vector autoregression to explore what happens following a technology shock.

My analysis is closest in spirit to Shea's (1998) study in which the author uses the number of patent applications and R&D expenditures as direct indicators of technological change. However, I find that my new indicators are better able to capture movements in TFP, capital and labor than the more traditional patent and R&D indicators.

My results are consistent with the predictions of the standard real business cycle models and sticky price models where the monetary authority accommodates a technology shock by increasing the money supply. Specifically, I find that, in response to a positive technology shock, GDP, TFP, labor and capital increase. However, I fail to find overwhelming evidence that technology shocks are able to account for a large portion of the variation in labor seen at business cycle frequencies. Only telecommunications technology appears to have a significant impact on hours in the short run. Instead, the short run fluctuations in GDP are caused by the technology shock's affect on TFP and capital.

Changes in computer and telecommunications technology seem to have the largest effects on GDP. However, this may be due to the fact that my new indicators are more likely to capture product innovation technologies that will be used by a large number of individuals.

Given that the results suggest that new book indicators may provide good proxies for technological change in some areas, future work should concentrate on: (1) examining other subgroups of technology in an attempt to determine which other types of innovations may have an impact on economic activity, (2) determining if these results hold for other countries, (3) exploring the relationship between these new indicators and other technology indicators based on hedonic price indices, and (4) redoing this analysis using industry panel data to determine which sectors are most influenced by the type of technological changes captured by the new indicators.

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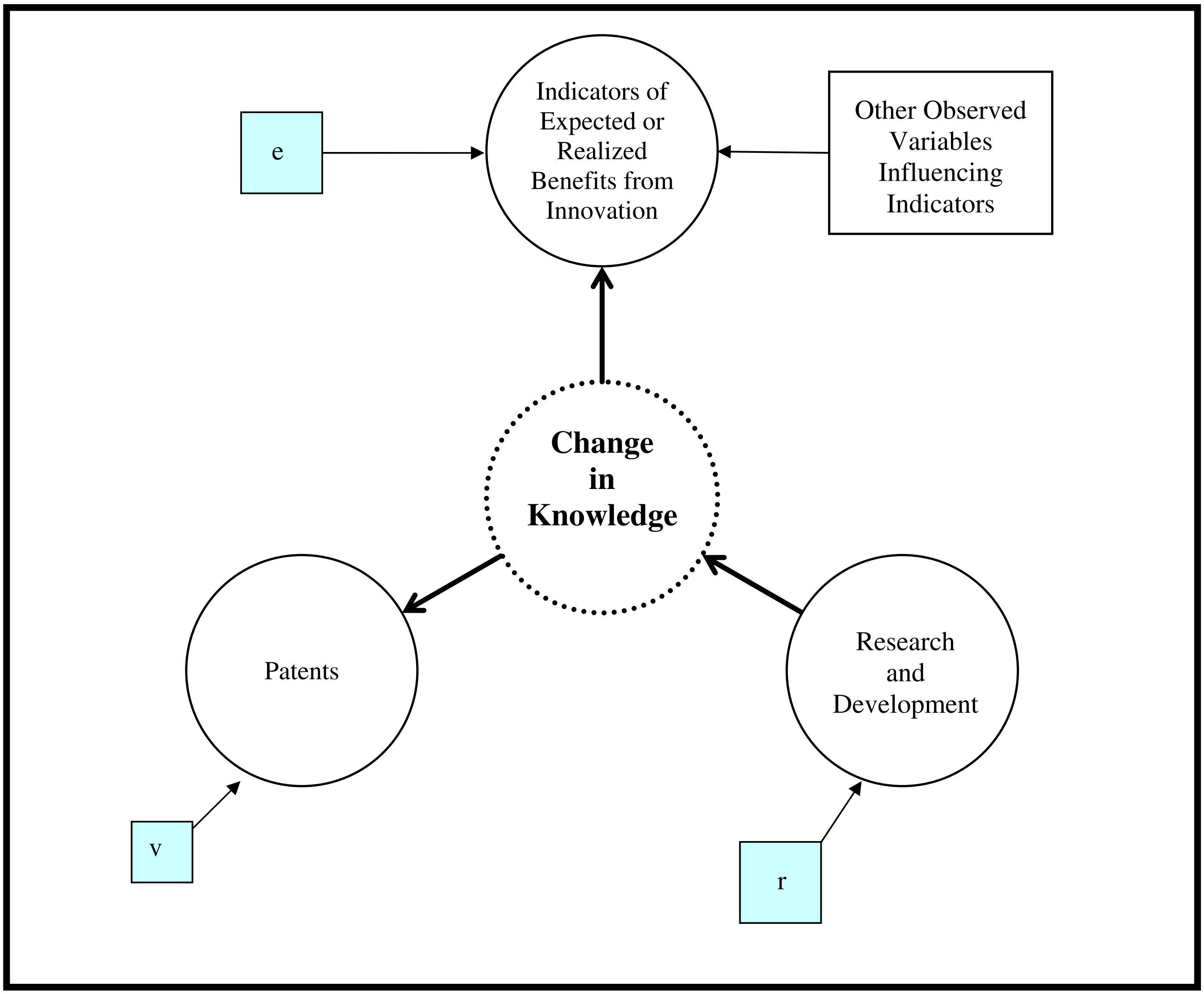
Figure 1. The Knowledge Production Function (Griliches)
A Simplified Path Analysis Diagram



Here v, r, and e represent shocks to patents, research and development and measures of economic activity like GDP respectively.

Figure 2.

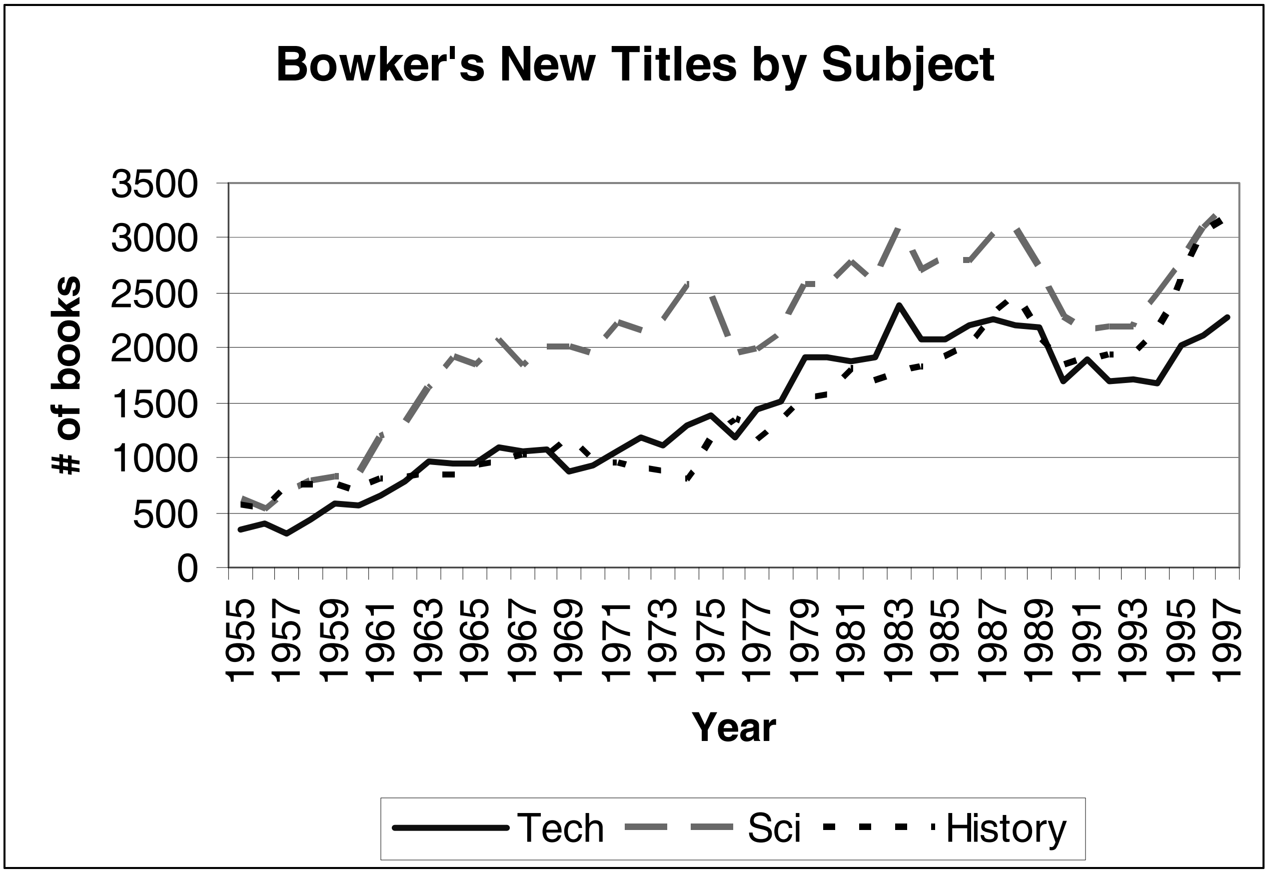

Bowker's New Titles by Subject
# of books
3500
3000
2500
2000
1500
1000
500
0
1955
1957
1959
1961
1963
1965
1967
1969
1971
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
Year
Tech
Sci
History

Figure 3. Sample Marc Record and Associated online display

Marc Record:


```
00971cam  2200277 a
4500001000800000005001700008008004100025035002100066906004500087010001700 1
320200039001490400018001880500027002060820017002331000024002502450055002 74
260004600329300002700375440004600402504002500448500002000473650003600493 74
000380052995200600056799100660062 7-2860358-20000328102341.0-850830s1986
mau      b    001 0 eng  -  9(DLC)   85020087-  a7bcbccorignewd1eocipf19-
gy-gencatlg-  a   85020087 -  a020112078X (pbk.) :c$21.95 (est.)-  aDLC-
cDLCdDLC-00aQA76.73.C153bS77 1986-00a005.13/3219-1 aStroustrup,
Bjarne.-14aThe C++ programming language /cBjarne Stroustrup.-  aReading,
Mass. :bAddison-Wesley,cc1986.-  aviii, 327 p. ;c24 cm.- 0aAddison-Wesley
series in computer science-  aBibliography: p. 10.-  aIncludes index.- 0-
aC++ (Computer program language)-0 aC plus plus programming language.-  -
aAnother issue (not in LC) has: viii, 328 p. ta01 4-3-87-  bc-GenColl-
hQA76.73.C153iS77 1986p0003475293AtCopy 1wBOOKS-
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Online display of information in Marc Record:

The C++ programming language / Bjarne Stroustrup.

LC Control Number:	85020087
Type of Material:	Text (Book, Microform, Electronic, etc.)
Personal Name:	Stroustrup, Bjarne.
Main Title:	The C++ programming language / Bjarne Stroustrup.
Published/Created:	Reading, Mass. : Addison-Wesley, c1986.
Related Titles:	C plus plus programming language.
Description:	viii, 327 p. ; 24 cm.
ISBN:	020112078X (pbk.) :
Notes:	Includes index. Bibliography: p. 10.
Subjects:	C++ (Computer program language)
Series:	Addison-Wesley series in computer science
LC Classification:	QA76.73.C153 S77 1986
Dewey Class No.:	005.13/3 19

Figure 4. LOC Graph of Indicators

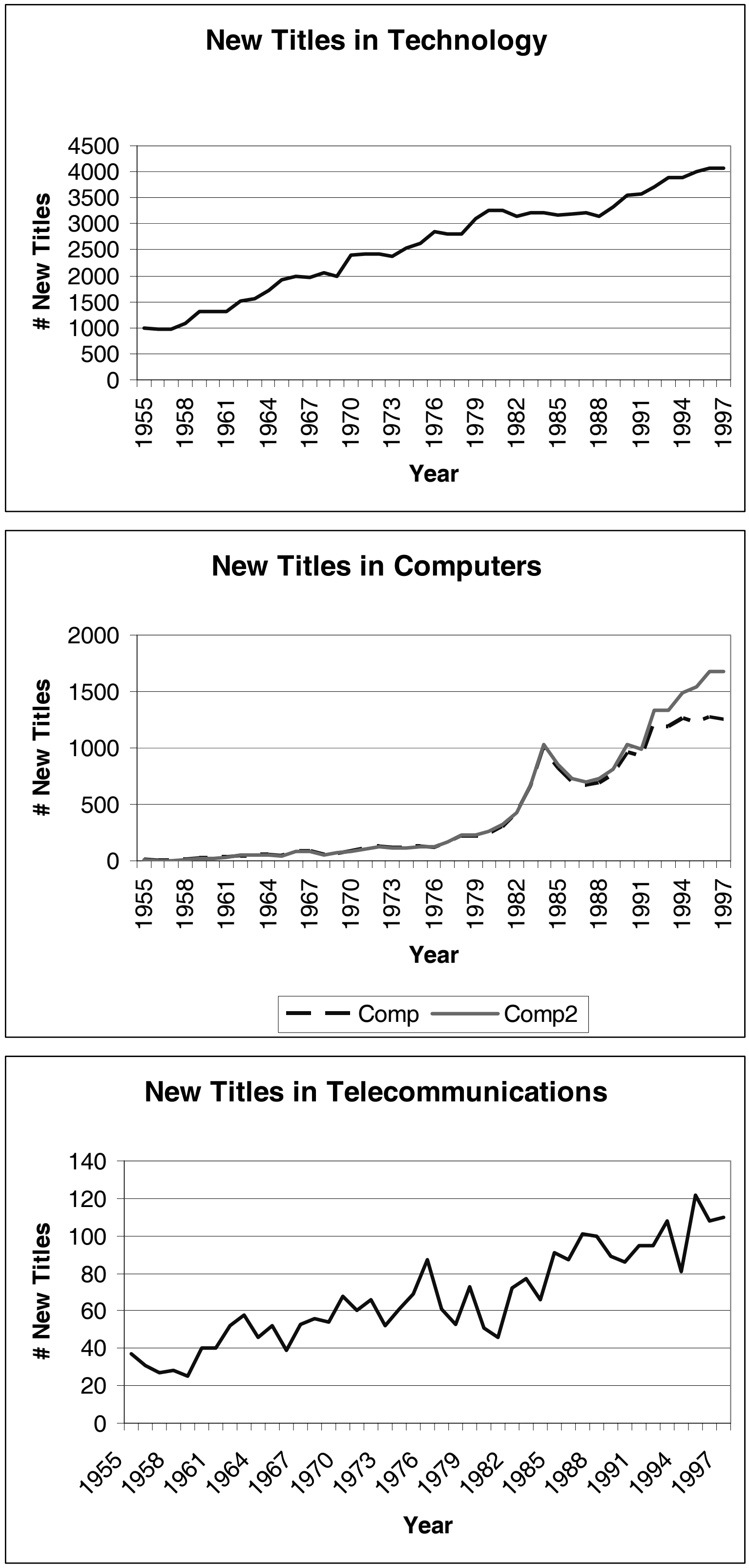


Figure 5. The Augmented Knowledge
Production Function
A Simplified Path Analysis Diagram

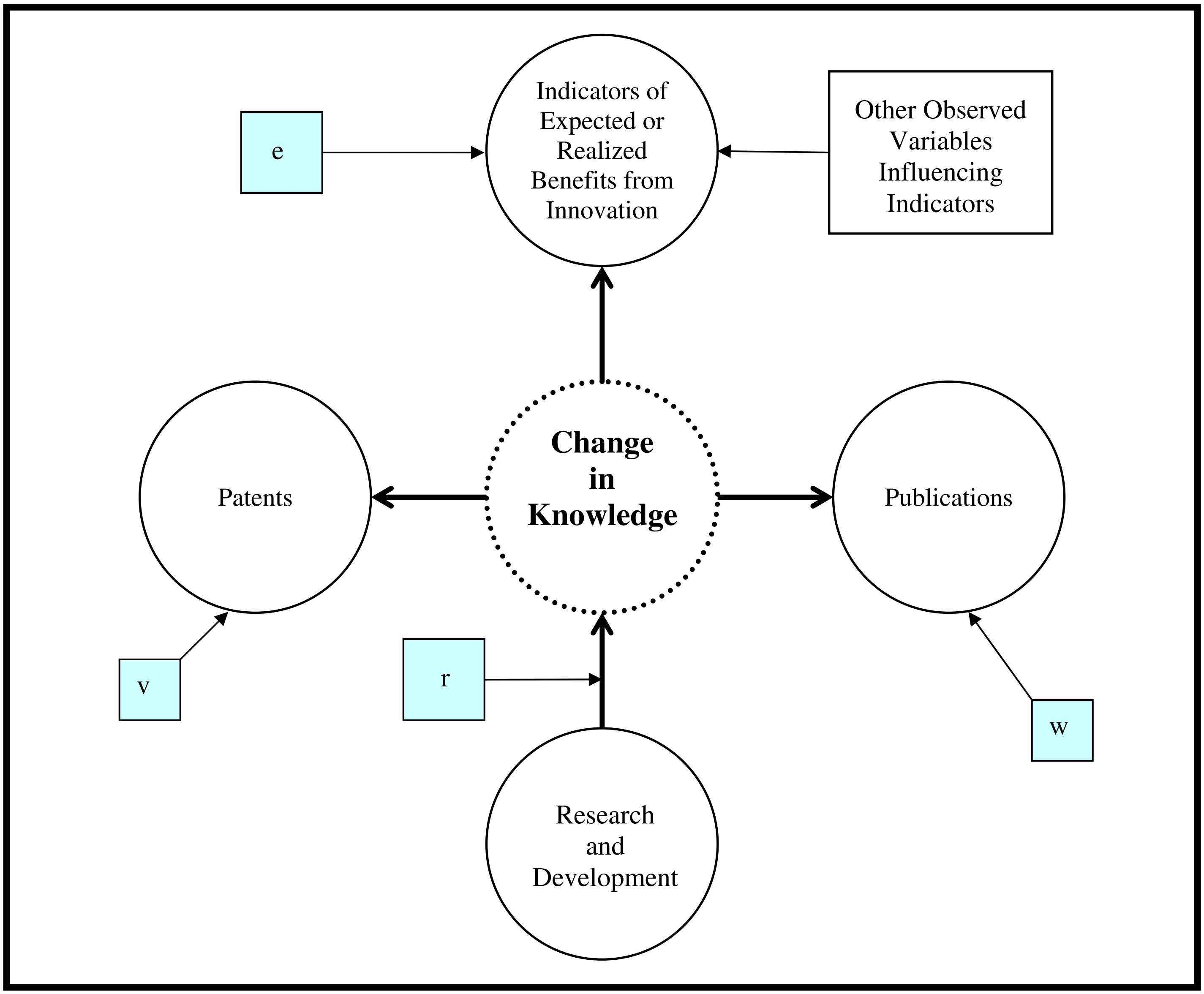
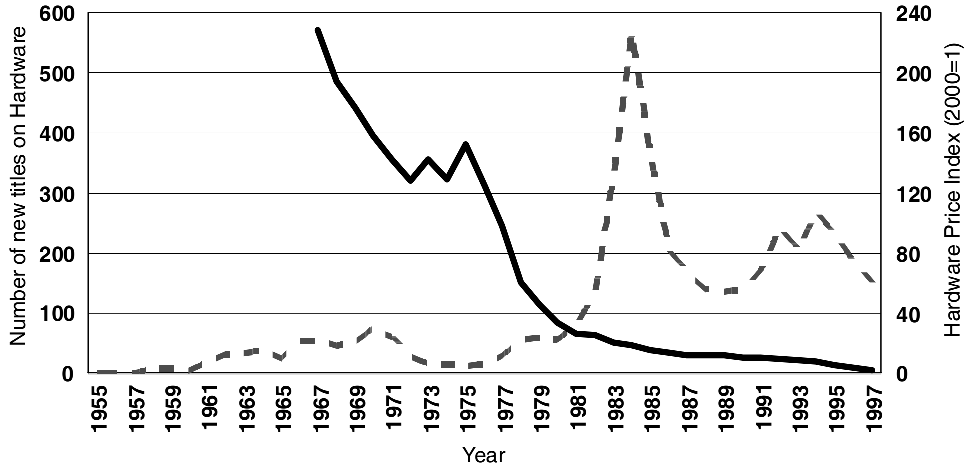


Figure 6A. New Hardware Titles and Timeline



Timeline with Major dates

1955	Computers introduced: IBM702, Norc, Monorobot III
1956	IBM builds 1st hard drive cost: $1,000,000
1957	IBM introduces RAMAC Storage system
1958	Commercial Transistor Computers make first appearance
1959	Beginning of second generation of computers
1960	IBM releases IBM360 computer & DEC introduces computer with keyboard and monitor ($120,000) and first mini-computer ($20,000)
1961	First commercially integrated circuit introduced & IBM 7030 marketed
1962	Magnetic storage tape introduced & input output system using punch-tape terminal
1964	First Super computer introduced (CRAY)
1965	DEC introduces new mini-computer ($18,500)
1966	IBM introduces fist disk storage system
1967	floppy disk invented
1969	Intel announces first 1KB Ram chip
1970	First Floppy disk Available & Daisy wheel printer
1971	First Mass produced Microprocessor (Intel 4004), First mini-computer kit and Intel introduces DRAM
1972	Intel 8008 processor released, hand held calculators become popular, and liquid crystal display introduced
1973	
1974	The Intel 8080 processor is introduced and becomes the basis for the first personal computers
1975	Altair computer introduced for $397 and becomes overnight success and IMSAI introduced as business computer
1977	Apple II computer is introduced at trade show along with TRS-80 and Commodore computers
1978	Office Automation is marketed by Wang and Intel introduces 8086 and 8088 chips
1979	Motorola introduces chip that will be used for Macintosh computers later
1980	First Portable computer introduced
1981	First IBM PC introduced, cost of RAM dropping rapidly, Intel develops much faster 80286
1982	First IBM clones introduced
1983	First laptop computer, IBM launches IBM/XT and IBM/AT, Apple launches Lisa computer
1984	Apple introduces Macintosh computer, commodore introduces AMIGA and Intel ships 80286 chips
1985	Intel 80386 chip introduced
1986	First computer using new 80386 chip sold
1988	Nextcube computer introduced
1989	First 80486 computer chip by Intel
1990	New Cray super computers introduced and new chips developed by Motorola
1991	Archie telnet data retrieval system introduced
1992	World Wide Web launched
1993	Power PC introduced and Intel develops Pentium chip
1995	Pentium Pro chip introduced

Figure 6B.

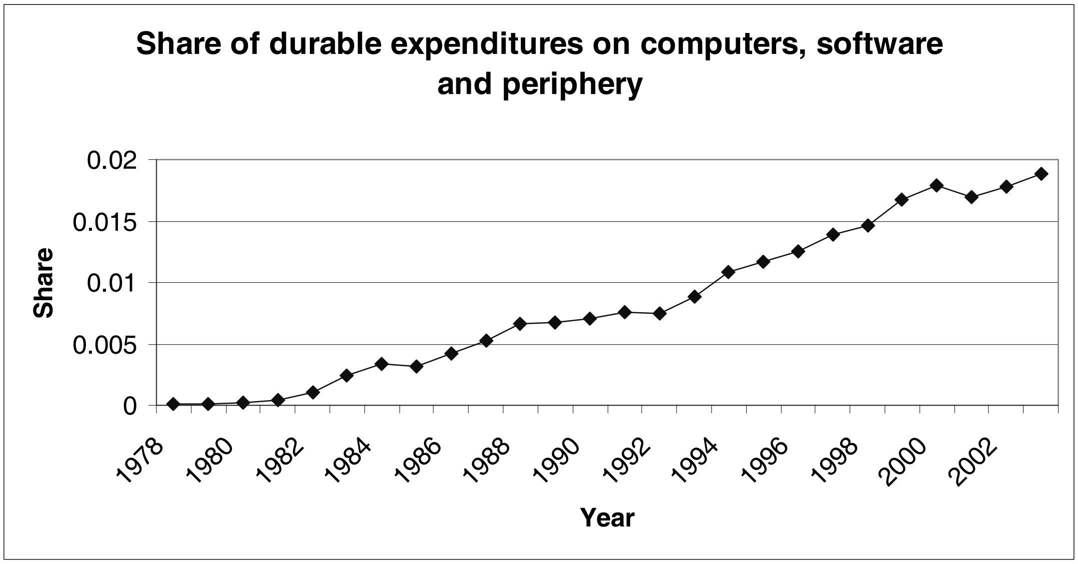


Figure 6C.

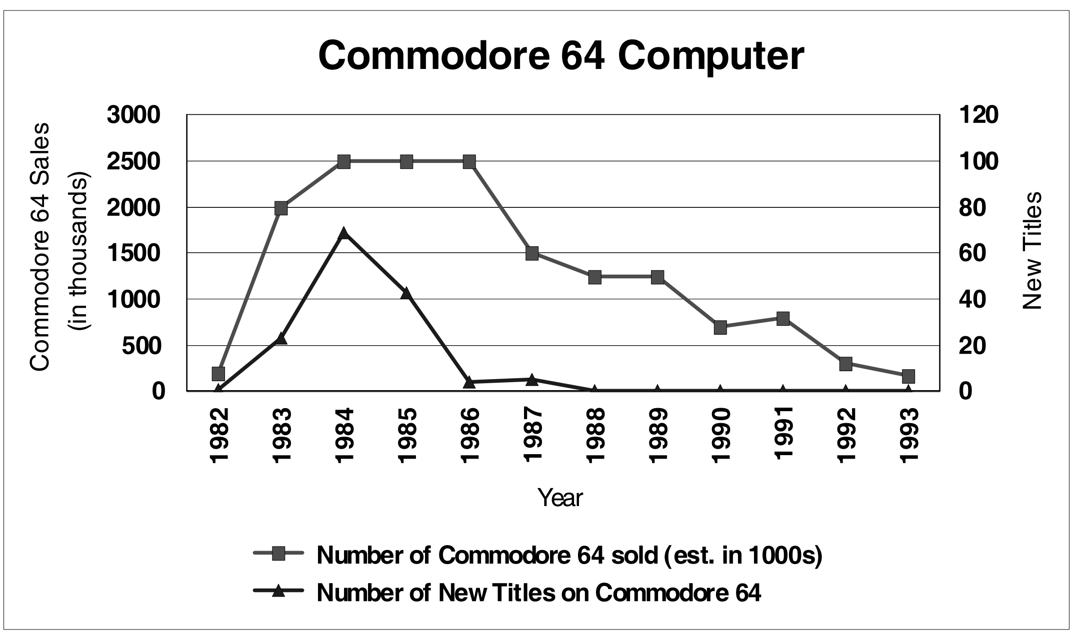


Figure 6D.

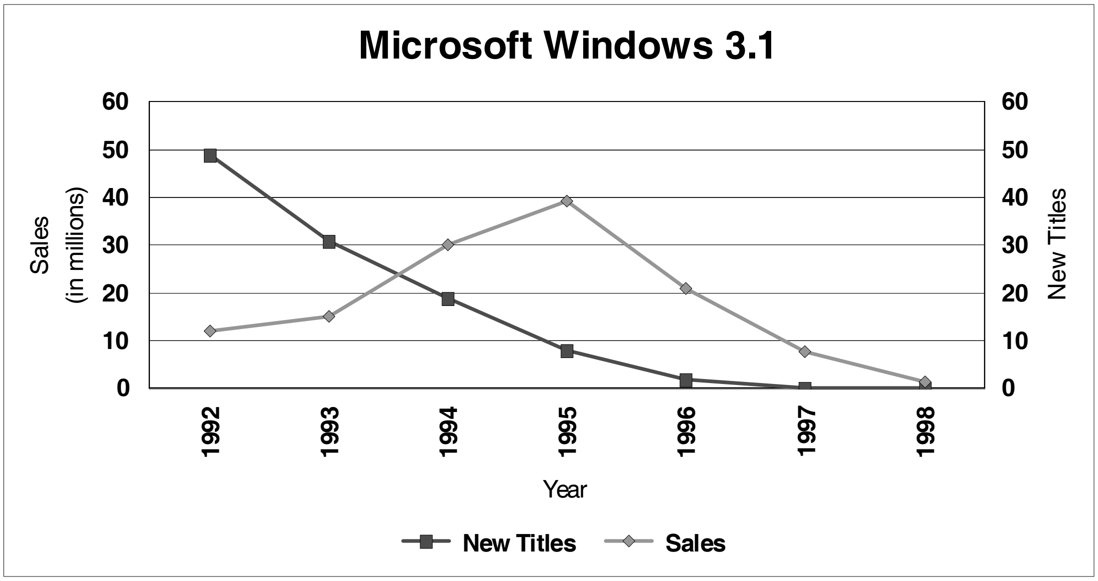
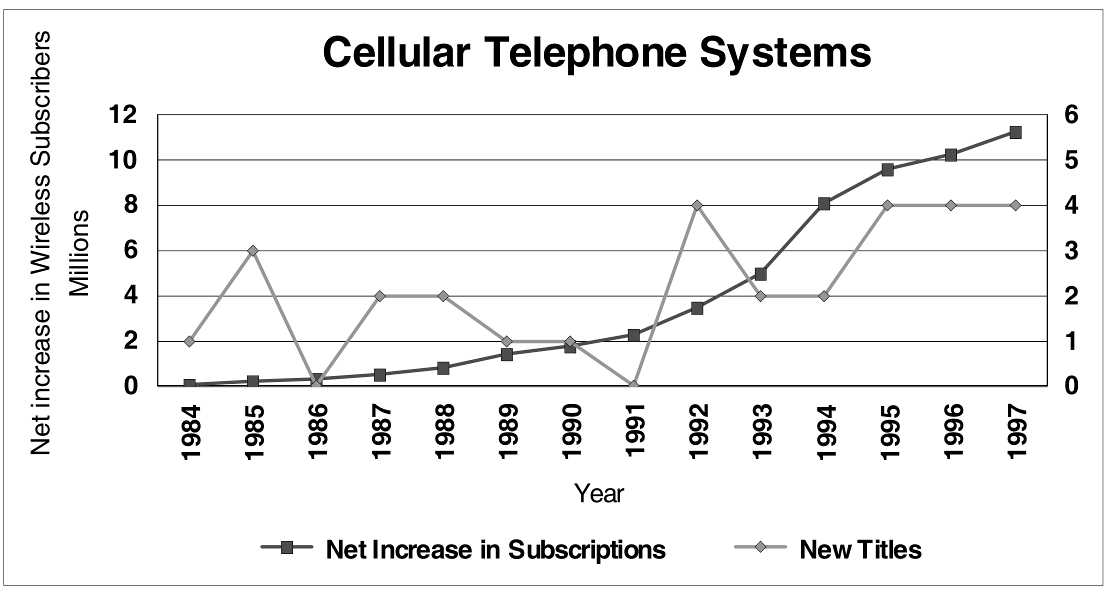
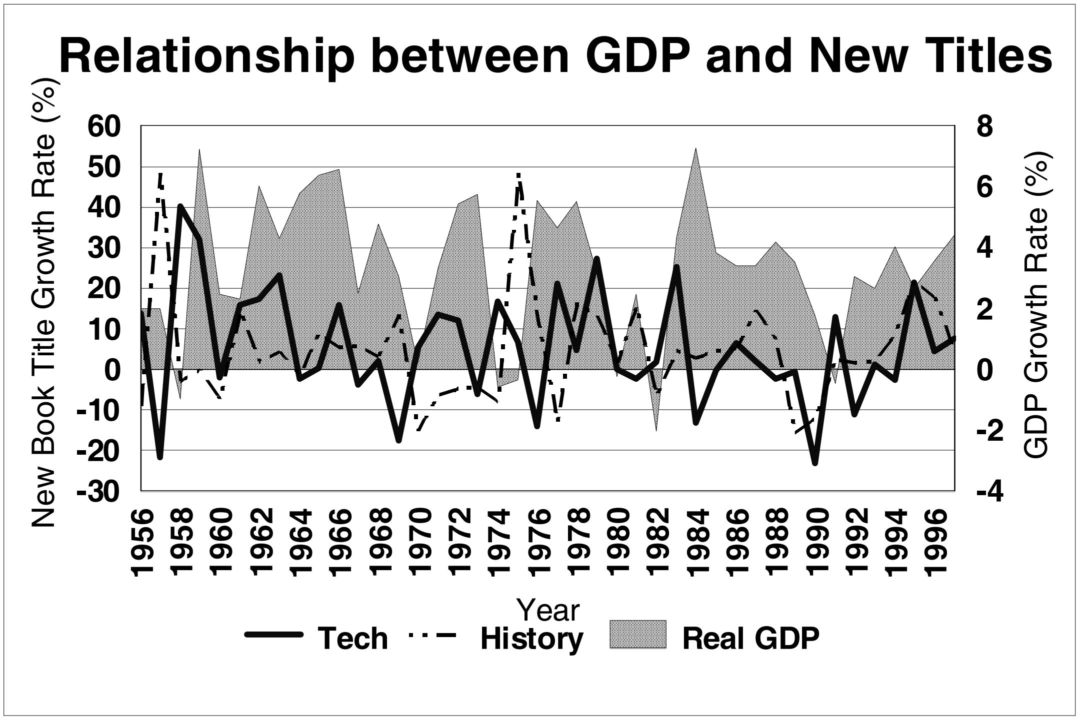


Figure 6E.



Note: In 1992 and 1993 there were major changes in cellular technology. The first commercial text message was sent in 1992 and in 1993 Bell Labs developed the digital Signal Processor for use in millions of handsets.

Figure 7.



Relationship between GDP and New Titles
New Book Title Growth Rate (%)
60
50
40
30
20
10
0
-10
-20
-30
8
6
4
2
0
-2
-4
GDP Growth Rate (%)
1956
1958
1960
1962
1964
1966
1968
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
Year
Tech
History
Real GDP

Figure 8. Impulse Responses of Ln(GDP) to Positive Technology Shocks

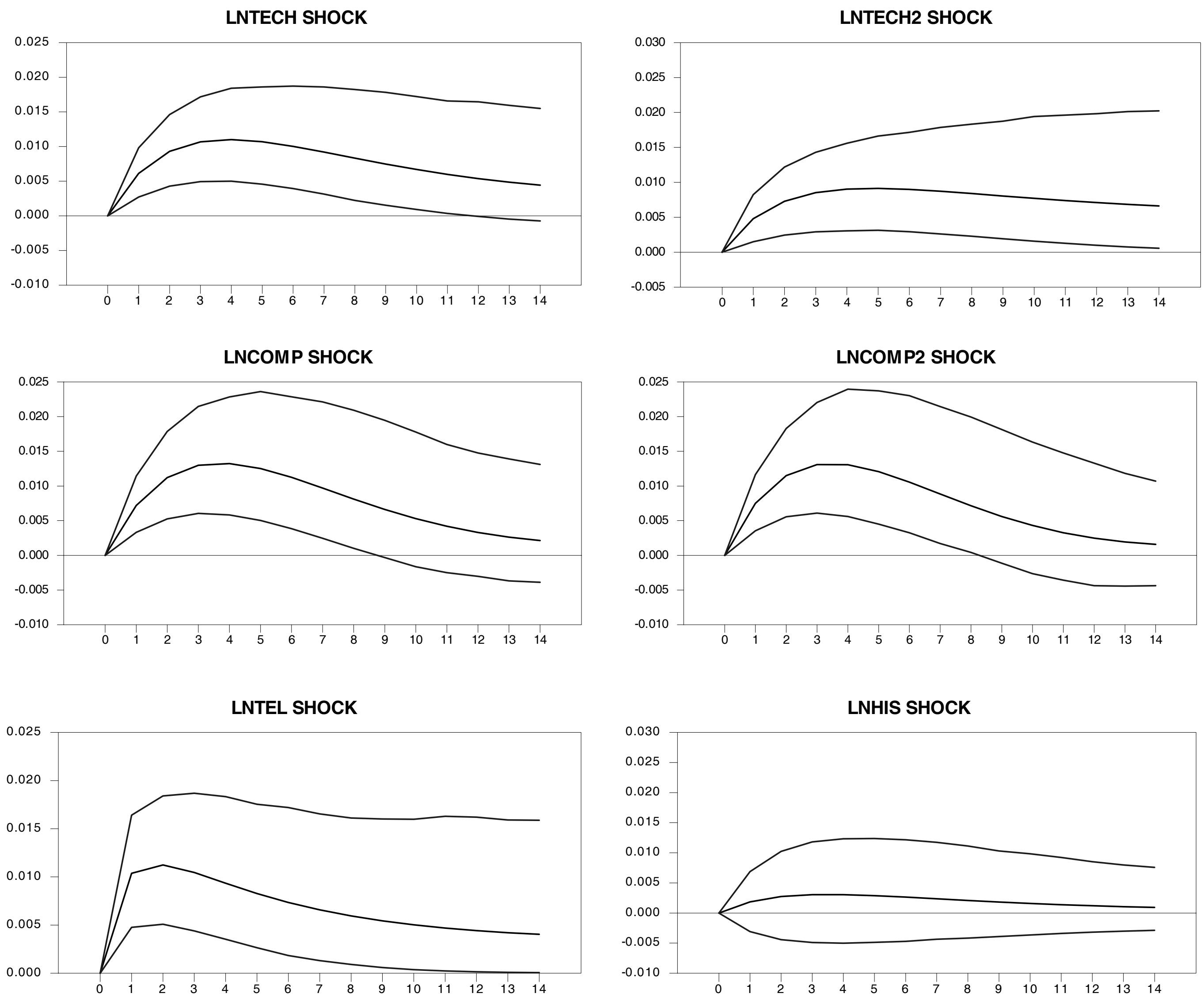


Figure 9. Responses of TFP Measure 1 to Positive Technology Shocks

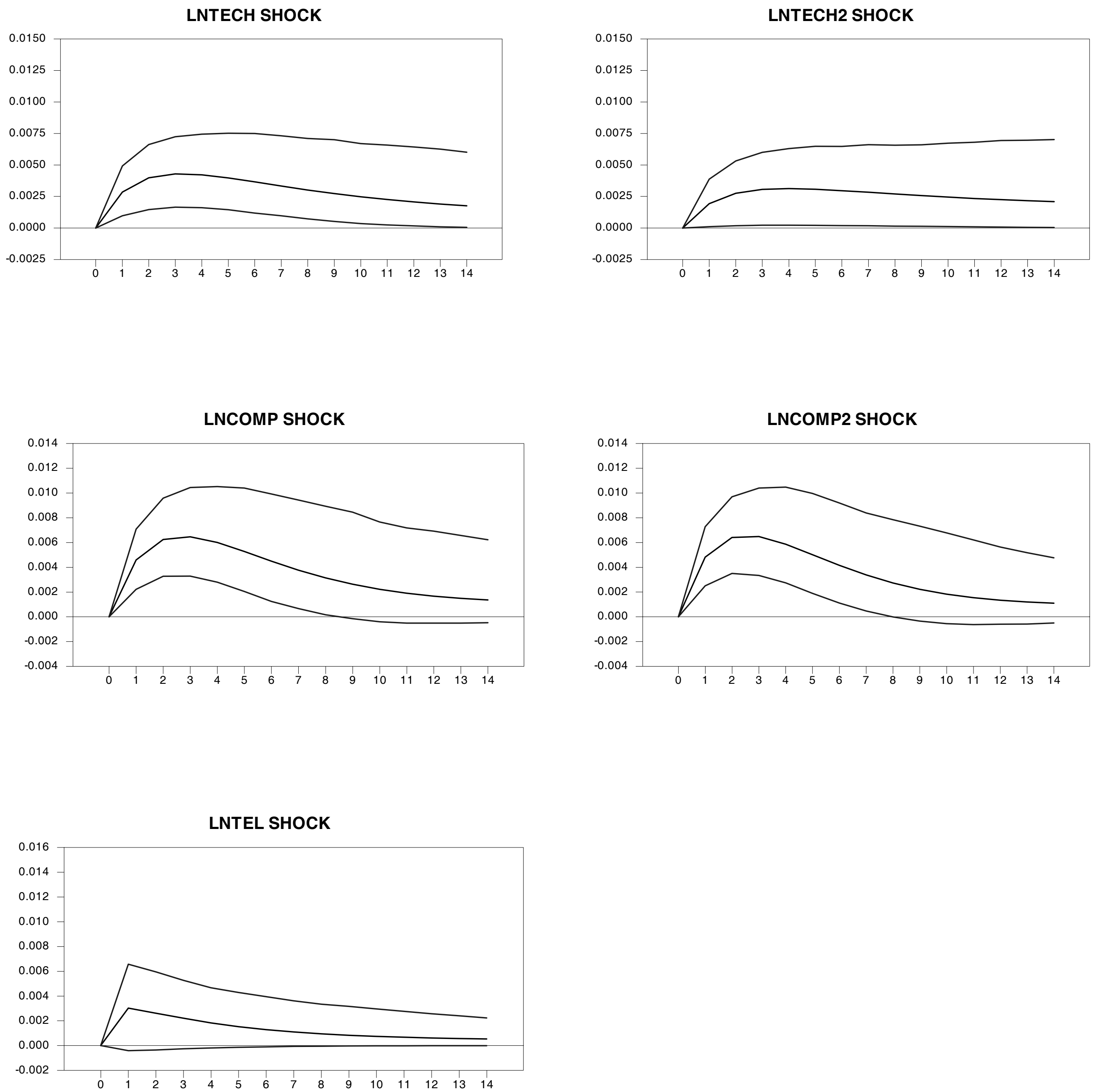


Figure 10. Responses of TFP Measure 2 to Technology Shocks

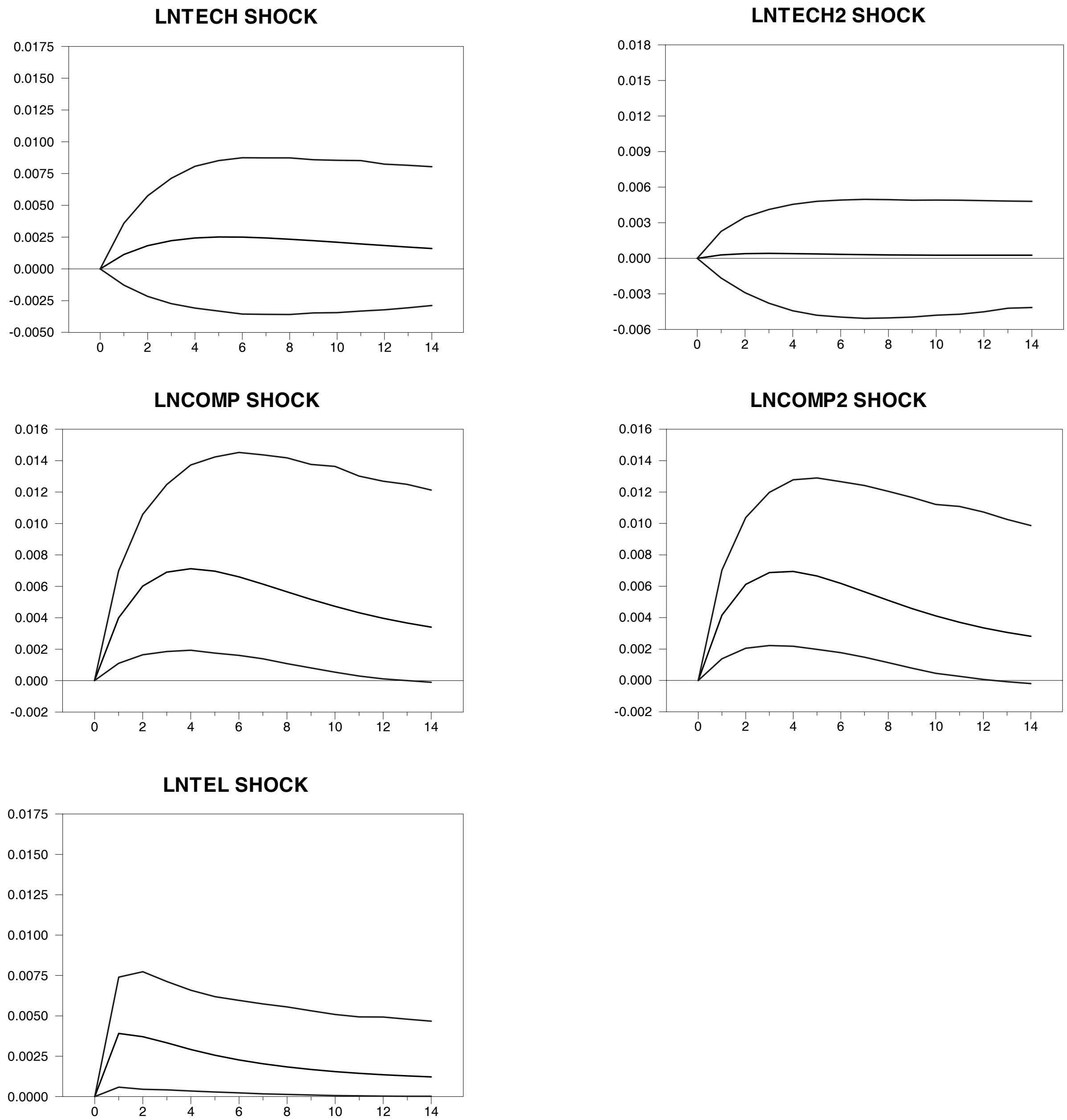


Figure 11. Impulse Response Functions for Four Variable VAR using TFP Measure 1

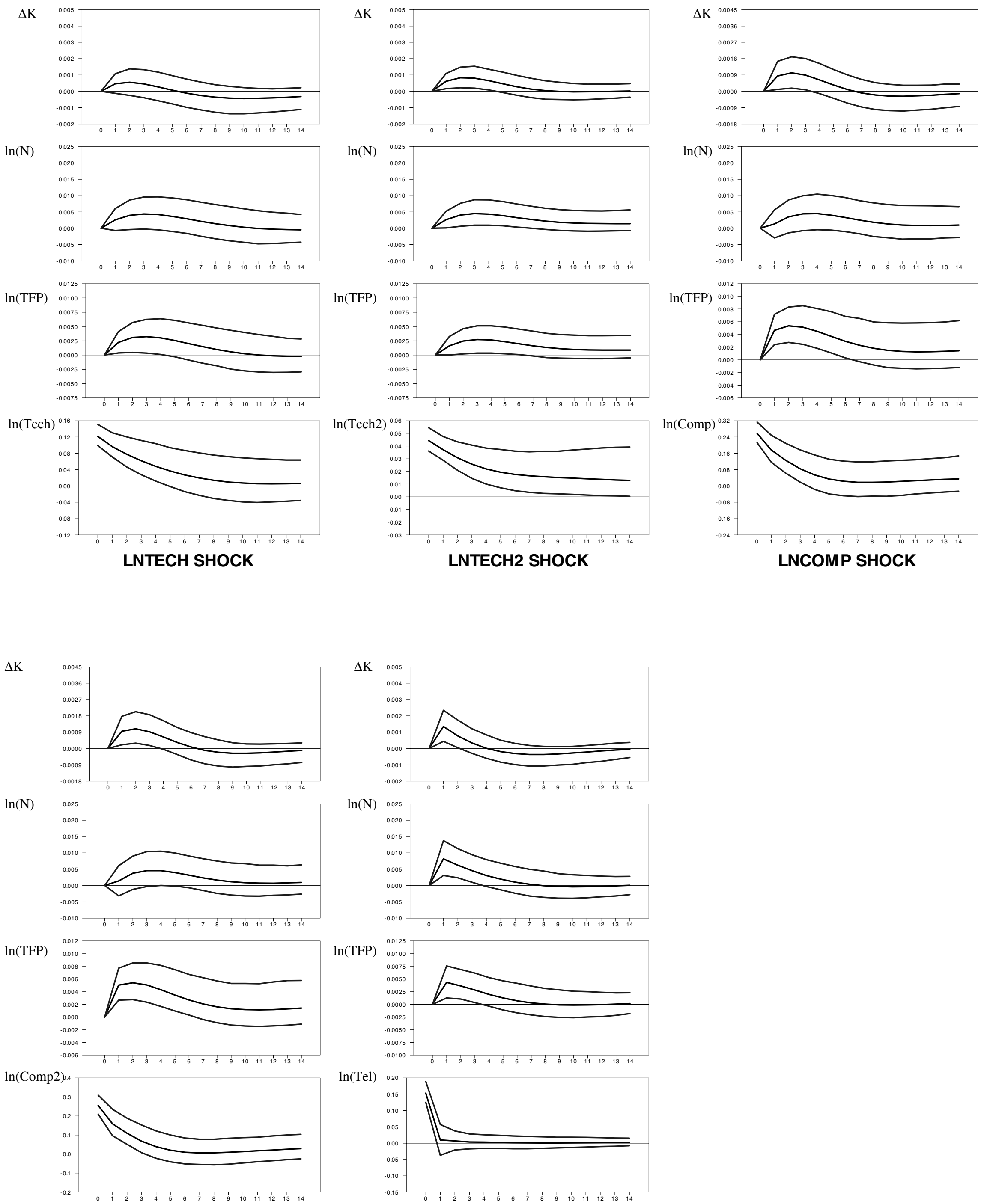


Figure 12. Impulse Response Functions for Four Variable VAR using TFP Measure 2

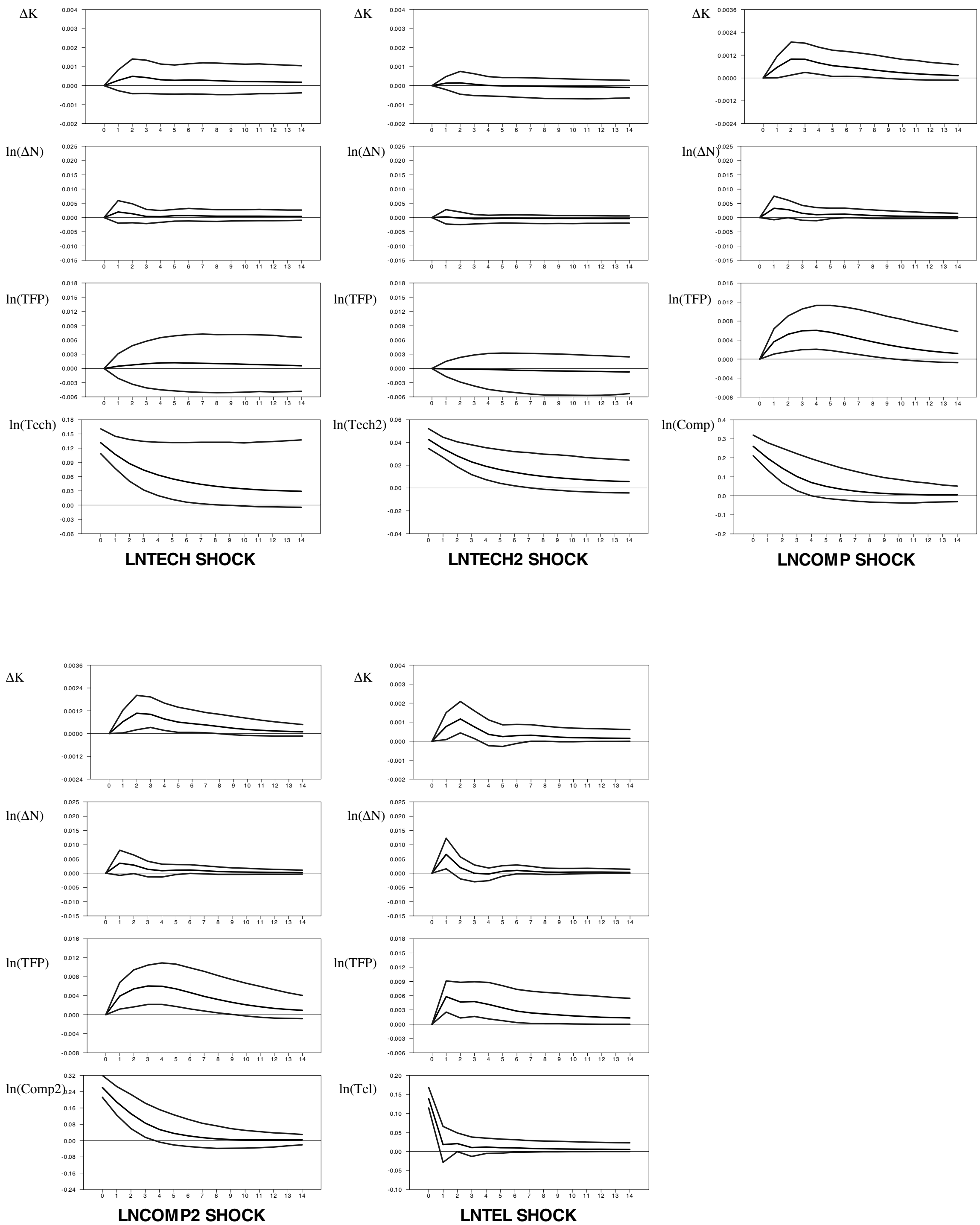


Table 1. Relationship between Science and Technology

Indicator	Does Science Granger-cause Technology?		Does R&D Granger-cause Technology?		Do Patents Granger-cause Technology?	
	P-Value	Lag Length	P-Value	Lag Length	P-Value	Lag Length
Bowker's New Tech Books (TECH)	0.049	1	0.230	2	0.221	1
Computer Software & Hardware Books (COMP)	0.022	2	0.074	1	0.083	3
Computer Software, Hardware & Network Books (COMP2)	0.012	2	0.058	1	0.188	2
Telecommunications (TEL)	0.038	1	0.016	1	0.702	2
LOC New Tech Books (TECH2)	0.016	1	0.023	2	0.327	2
Indicator:	Does the Indicator Granger-cause Science?		Does the Indicator Granger-cause R&D ?		Does the Indicator Granger-cause Patents?	
	P-Value	Lag Length	P-Value	Lag Length	P-Value	Lag Length
Bowker's New Tech Books (TECH)	0.558	1	0.095	2	0.406	1
Computer Software & Hardware Books (COMP)	0.061	2	0.015	2	0.761	2
Computer Software, Hardware & Network Books (COMP2)	0.037	2	0.014	2	0.733	2
Telecommunications (TEL)	0.219	2	0.600	4	0.293	4
LOC New Tech Books (TECH2)	0.038	3	0.038	1	0.023	1

Table 2: Relationship Between GDP and Technology Growth Rates in the Short Run

X	Estimate of β_1 (1)	(2)	(3)
Bowker's New Tech Books	0.0856^{***}	-0.0008	-0.0077
(TECH)	(0.0225)	(0.0253)	(0.0262)
Computer Software and Hardware Books	0.0267^{*}	0.0031	-0.0011
(COMP)	(0.0143)	(0.0115)	(0.0119)
Computer Software, Hardware & Network Books	0.0257^{*}	0.0053	-0.0005
(COMP2)	(0.0151)	(0.0116)	(0.0119)
Library of Congress New Tech Books	0.2089^{***}	0.0460	0.0362
(TECH2)	(0.0357)	(0.0617)	(0.0629)
Telecommunications	0.0433	-0.0038	-0.0304^{*}
(TEL)	(0.0339)	(0.0180)	(0.0158)
Patents	-0.1424^{**}	0.0020	0.0077
(PAT)	(0.0564)	(0.0829)	(0.0781)
Research &Development Expenditures	0.0961^{*}	0.1825^{*}	0.0802
(RANDD)	(0.0491)	(0.1003)	(0.0698)
Bowker's new Science Books	0.0943^{***}	0.0092	0.0091
(SCI)	(0.0171)	(0.0276)	(0.0291)
Bowker's new History Books	-0.0317	0.0081	0.0039
(HIS)	(0.0452)	(0.0325)	(0.0291)

(1) $\ln(GDP_t)=\alpha+\beta_1\ln(X_t)+\gamma t+\varepsilon_t$

(2) $\ln(GDP_t)=\alpha+\beta_1\ln(X_t)+ \beta_2\ln(X_{t-1})+ \beta_3\ln(GDP_{t-1}) +\gamma t+\varepsilon_t$

(3) $\Delta\ln(GDP_t)=\alpha+\beta_1\Delta\ln(X_t)+\varepsilon_t$

*** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level

Table 3: Granger-Causality
Tests: P-Values

Technology Indicator	Does Technology Granger-Cause GDP?	Does GDP Granger-Cause Technology?	Does Technology Granger-Cause TFP?		Does TFP Grange-Cause Technology?	
			Measure 1	Measure 2	Measure 1	Measure 2
Bowker's New Tech Books (TECH)	0.004	0.805	0.012	0.412	0.671	0.868
Computer Software & Hardware Books (COMP)	0.002	0.282	0.001	0.018	0.718	0.928
Computer Software, Hardware & Networks (COMP2)	0.002	0.237	0.001	0.015	0.731	0.886
Library of Congress New Tech Books (TECH2)	0.015	0.872	0.081	0.808	0.686	0.052
Telecommunications (TEL)	0.002	0.467	0.127	0.053	0.043	0.062
Patents (PAT) 4 lags	0.570	0.588	0.829	0.100	0.571	0.502
Research & Development (RANDD) 4 lags	0.863	0.318	0.044	0.020	0.362	0.549
Bowker's New Science Books (SCI) 2 lags	0.002	0.931	0.040	0.471	0.571	0.773
Bowker's new History Books (HIS)	0.528	0.275	0.542	0.285	0.177	0.163

Table 4. Percent of Variation Due to Technology in Two Variable VARs

Variance Decomposition

	Years	ln(GDP)	ln(TFP1)	ln(TFP2)
Bowker's New Tech Books	3	15.02	11.07	1.13
(TECH)	6	37.59	27.58	3.92
	9	46.68	34.35	6.22
Computer Software & Hardware Books	3	18.41	26.04	13.30
(COMP)	6	42.25	48.20	30.76
	9	49.55	52.63	38.03
Computer Software, Hardware & Networks Books	3	18.84	27.21	14.00
(COMP2)	6	40.99	47.78	30.63
	9	47.02	51.38	37.05
Library of Congress New Tech Books	3	9.42	4.75	0.07
(TECH2)	6	27.43	13.97	0.24
	9	37.67	19.50	0.39
Telecommunications	3	22.61	5.43	5.85
(TEL)	6	30.73	6.87	7.10
	9	32.67	7.13	7.41
Patents	3	5.53	0.06	11.75
4 lags	6	5.03	3.89	13.68
(PAT)	9	5.06	5.15	14.17
R&D	3	0.39	10.26	3.46
4 lags	6	0.83	14.11	12.61
(RANDD)	9	2.55	21.27	31.44
Bowker's new Science Books	3	8.07	3.96	1.73
2 lags	6	35.86	16.76	7.16
(SCI)	9	41.05	22.06	10.56

Table 5: Relationship Between TFP and Technology Growth Rates in the Short Run

X	Estimates of β_1					
	Measure 1			Measure 2		
	(1)	(2)	(3)	(1)	(2)	(3)
Bowker's New Tech Books	0.0365***	-0.0222	-0.0248	0.0652***	0.0126	0.0160
(TECH)	(0.0112)	(0.0143)	(0.0149)	(0.0180)	(0.0170)	(0.0163)
Computer Software & Hardware Books	0.0191***	-0.0040	-0.0053	0.0352***	0.0023	0.0004
(COMP)	(0.0065)	(0.0063)	(0.0069)	(0.0106)	(0.0073)	(0.0075)
Computer Software, Hardware & Network Books (COMP2)	0.0198***	-0.0030	-0.0051	0.0361***	0.0026	-0.0003
	(0.0068)	(0.0063)	(0.0069)	(0.0111)	(0.0073)	(0.0075)
Library of Congress New Tech Books	0.0986***	0.0441	0.0413	0.1584***	-0.0062	0.0001
(TECH2)	(0.0174)	(0.0358)	(0.0364)	(0.0294)	(0.0433)	(0.0398)
Telecommunications	0.0396**	0.0086	-0.0043	0.0899***	0.0388***	0.0132
(TEL)	(0.0154)	(0.0117)	(0.0097)	(0.0230)	(0.0106)	(0.0102)
Patents	-0.0239	0.0267	0.0207	-0.0241	0.0008	-0.0223
(PAT)	(0.0289)	(0.0466)	(0.0456)	(0.0500)	(0.0518)	(0.0506)
Research &Development	0.0895***	0.0346	0.0525	0.1554***	-0.0440	0.0245
(RANDD)	(0.0202)	(0.0575)	(0.0407)	(0.0317)	(0.0590)	(0.0444)
Bowker's new Science Books	0.0473***	0.0015	-0.0038	0.0817***	0.0198	0.0216
(SCI)	(0.0079)	(0.0164)	(0.0170)	(0.0121)	(0.0185)	(0.0180)
Bowker's new History Books	-0.0232	-0.0043	-0.0032	-0.0305	0.0073	0.0014
(HIS)	(0.0216)	(0.0185)	(0.0170)	(0.0359)	(0.0199)	(0.0183)

(1) $\ln(TFP_t)=\alpha+\beta_1\ln(X_t)+\gamma t+\varepsilon_t$

(2) $\ln(TFP_t)=\alpha+\beta_1\ln(X_t)+\beta_2\ln(X_{t-1})+\beta_3\ln(TFP_{t-1})+\gamma t+\varepsilon_t$

(3) $\Delta\ln(TFP_t)=\alpha+\beta_1\Delta\ln(X_t)+\varepsilon_t$

*** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level

Table 6: Granger-Causality Tests for the Four variable VAR using TFP Measure 1: P-Values

Technology Indicator	Does Technology Granger-Cause		
	$\Delta\ln(K)$	$\ln(L)$	$\ln(TFP)$
Bowker's New Tech Books (TECH)	0.1674	0.1651	0.0478
Computer Books (COMP)	0.0517	0.5946	0.0009
Computer Books (COMP2)	0.0354	0.5887	0.0005
Library of Congress New Tech Books (TECH2)	0.0194	0.0749	0.0712
Telecommunications (TEL)	0.0119	0.0055	0.0173
Do Inputs and TFP Granger -Cause Technology?			
	$\Delta\ln(K)$	$\ln(L)$	$\ln(TFP)$
Bowker's New Tech Books (TECH)	0.4698	0.0825	0.6054
Computer Books (COMP)	0.5414	0.1853	0.3406
Computer Books (COMP2)	0.7651	0.1019	0.3543
Library of Congress New Tech Books (TECH2)	0.1410	0.5998	0.2005
Telecommunications (TEL)	0.7401	0.0400	0.0400

Table 7: Granger-Causality Tests for the Four variable VAR using TFP Measure 2: P-Values

Technology Indicator	Does Technology Granger-Cause		
	$\Delta\ln(K)$	$\Delta\ln(L)$	$\ln(TFP)$
Bowker's New Tech Books (TECH)	0.3513	0.3686	0.7312
Computer Books (COMP)	0.0840	0.1778	0.0160
Computer Books (COMP2)	0.0618	0.1579	0.0125
Library of Congress New Tech Books (TECH2)	0.4978	0.8549	0.9114
Telecommunications (TEL)	0.0557	0.0251	0.0017
Do Inputs and TFP Granger -Cause Technology?			
	$\Delta\ln(K)$	$\Delta\ln(L)$	$\ln(TFP)$
Bowker's New Tech Books (TECH)	0.8241	0.4463	0.8868
Computer Books (COMP)	0.1719	0.7151	0.6262
Computer Books (COMP2)	0.1562	0.8324	0.5934
Library of Congress New Tech Books (TECH2)	0.2074	0.7948	0.0511
Telecommunications (TEL)	0.6874	0.7211	0.1372

Table 8. Variation Due to Technology in the Four-Variable VAR with TFP Measure 1

	Years	Δln(K)	ln(L)	ln(TFP)
Bowker's New Tech Books	3	2.66	3.59	6.51
(TECH)	6	3.70	10.17	15.49
	9	4.41	11.52	16.92
Computer Software & Hardware Books	3	9.22	2.00	23.25
(COMP)	6	13.94	9.16	38.51
	9	13.44	11.04	40.34
Computer Software,	3	10.93	2.23	24.94
Hardware & Networks	6	15.34	9.21	38.25
(COMP2)	9	14.81	10.70	39.57
Library of Congress New Tech Books	3	5.80	3.96	3.99
(TECH2)	6	10.41	11.77	11.93
	9	10.27	14.25	14.38
Telecommunications	3	11.33	16.37	11.74
(TEL)	6	10.65	17.10	12.78
	9	11.76	16.87	12.63
Patents (PAT)	3	2.64	9.18	1.34
4 lags	6	6.03	7.07	9.64
	9	5.98	7.81	9.57

Table 9. Variation Due to Technology in the Four-Variable VAR with TFP Measure 2

	Years	Δln(K)	Δln(L)	Ln(TFP)
Bowker's New Tech Books	3	1.778	0.989	0.227
(TECH)	6	3.285	1.033	1.206
	9	4.038	1.156	2.108
Computer Software & Hardware				
Books	3	8.113	3.378	13.931
(COMP)	6	16.478	3.958	32.515
	9	18.724	4.266	38.336
Computer Software, Hardware	3	9.209	3.644	14.931
& Networks	6	17.022	4.064	32.608
(COMP2)	9	18.813	4.313	37.522
Library of Congress New Tech Books	3	0.228	0.016	0.005
(TECH2)	6	0.255	0.046	0.004
	9	0.267	0.047	0.004
Telecommunications	3	10.338	8.024	12.959
(TEL)	6	11.216	7.965	15.754
	9	11.541	8.073	16.131
Patents (PAT)	3	1.131	5.996	10.920
4 lags	6	2.506	12.796	11.209
	9	3.231	13.796	11.314

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

Subclass QA Mathematics
- QA71-90 Instruments and machines
- QA75-76.95 Calculating machines
- QA75.5-76.95 Electronic computers. Computer science
- QA76.75-76.765 Computer software