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Read All About it!! What happens following a technology shock?

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Abstract:

Existing indicators of technical change are plagued by shortcomings. I present here new measures based on books published in the field of technology that resolve many of these problems and use them to identify the impact of technology shocks on economic activity. They are positively linked to changes in R&D and scientific knowledge and capture the new technologies' commercialization dates. Changes in information technology are found to be important sources of economic fluctuations in the post-WWII period and total factor productivity, investment and, to a lesser extent, labor are all shown to increase following a positive technology shock. (JEL E32, O3)

Introduction

Economists have expended a tremendous amount of time and energy trying to identify the role played by technical change in economic growth and fluctuations. In spite of this prodigious effort, measurement continues to be a problem. Specialists in the field of Industrial Organization, for example, use data on research and development (R&D) intensity and patents as proxies of innovative activity even though they acknowledge that these measures are plagued by a number of serious problems, not least of which are the long and uncertain lags associated with their effects. Macroeconomists, in their attempt to pinpoint the impact of technology shocks on cyclical fluctuations, employ a variety of indirect measures of technical change including Solow residuals (purified or unpurified) and long run restrictions in structural vector autoregressions – in spite of their well known flaws.[1] In short, then, for want of better, we are forced to rely on second best indicators and to make do with debatable findings. This raises two obvious questions, first, what features would an ideal indicator possess and, second, are there any unutilized sources of data that could help us construct such a measure?

Most would agree that such an indicator should: (1) be available at least on an annual basis over a long time horizon, (2) be objectively determined, (3) be related to the date that a new product/process is brought to market, (4) weight different technologies according to their importance or impact on the economy, and (5) capture new technologies across a wide range of industries and firms. While a perfect index may always elude our grasp, I present in this paper new measures of technical change that, I argue, satisfy these criteria and resolve many of the problems associated with traditional ones. My annual measures are based on previously unexplored information on new book titles in the field of technology from 1955-97 obtainable from R.R. Bowker (a company that publishes lists of new titles available from major publishing houses) and the Library of Congress (the copyright depository for the U.S.). I show that these new measures are positively related to inputs into knowledge production (such as scientific advances and R&D), and correlate closely with the commercialization date of new technologies.

Once developed, I use the new indicators to help shed light on two hotly debated issues in the business cycle literature, first, the role of technology shocks in cyclical fluctuations and, second, the impact of

[1] See e.g., Basu et al. (2006) for a discussion of factors contaminating Solow residuals, and potential reasons why long-run identifying restrictions may capture both technology and non-technology shocks.

technological change on employment, productivity, and capital investment.[2] In a nutshell, I find that, while some innovations matter more than others, information technology has in the past 25 or so years had an important impact aggregate fluctuations while total factor productivity, capital investment and labor (albeit to a lesser extent) all increase following a positive technology shock. Among other things, these findings will aid us in model selection since they will help us determine which of the various business cycles models are consistent with the data.[3]

My paper, of course, is not the first that attempts to identify technology shocks and to evaluate their importance. There are, in fact, three basic approaches to these issues previously used in the literature. In the first, initially presented by Gali (1999), long-run restrictions in a structural vector autoregression (VAR) are used to identify the shocks.[4] In the second, Basu, Fernald and Kimball (BFK 2006) attempt 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 then use the corrected residual as the "true" measure of technology. Shea (1998), in the third, employs direct measures of technological change based on research and development expenditures (R&D) and patent activities in a VAR to identify technology shocks.[5]

While each of these has its strengths and its weaknesses,[6] my approach is closest to that of Shea (1998), with the obvious difference that I replace the traditional measures with my new ones. There are two main benefits to the use of direct measures. First, unlike Gali's (1999) approach, the results do not rely on the assumption that only technology shocks affect productivity in the long-run, an assumption that would be

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[2] See Gali and Rabanal (2004) for a review of the literature that attempts to answer these questions.

[3] Pinpointing the response of employment to technology shocks is likely to help us discriminate between competing business cycle models (for example, between a sticky price and a standard neoclassicial one) while information about the timing of TFP responses to the 'news' about new technologies (as picked up by new titles) should help us fine tune the type of models developed by Beaudry and Portier (2006) and Jaimovich and Rebelo (2006).

[4] This method is also seen in Gali and Rabanal (2004), Francis and Ramey (2005), Christiano, Eichenbaum and Vigfusson (CEV (2002, 2004)), Altig, Christiano, Eichenbaum and Linde (ACEL (2003)) and Fisher (2003).

[5] See also Christiansen 's (2008) work that examines the response of productivity and inputs in response to patent and R&D shocks.

[6] See Christiano, Eichenbaum and Vigfusson (2004) and Gali and Rabanal (2004) for an exploration of the strengths and weaknesses of the first, Shea (1998) and Christiano, Eichenbaum and Vigfusson (2004) for the second, and Gali (1998) and Jaffe (1998) for the third.

violated, for example, if growth is endogenous. Second, direct indicators sidestep many of the pitfalls- such as incomplete cleansing - associated with the corrected residual method of BFK (2006).

In spite of the similarity in our approach, my results differ from those of Shea (1998) – he finds a weak relationship between TFP and technology shocks while I find a strong one – largely because of the different indicators we use. There are, unfortunately, serious drawbacks to the traditional measures that Shea (1998) was compelled to adopt in his paper. In standard business cycle theory, a technology shock occurs only at the time when output is affected. The problem with using R&D expenditures or patents to identify these shocks is that factors, such as the time it takes to bring a new product to market, can cause long and indeterminate lags between inventive activity and any effect on output/productivity. [7] Shea's (1998) findings, in other words, are compromised by problems inherent in the use R&D and patents data to measure commercialization of innovations.[8] In contrast, new titles (excluding new editions) appear precisely when the innovation is first introduced to market, for the very good reason that the whole purpose of publications is to spread the word about the new product or process.[9] In short, then, my new indicators resolve the lag problem and approximate more closely what macroeconomists traditionally define as technology shocks.[10] Indeed, my results indicate that my new technology measures lead changes in productivity and GDP by approximately one year. Moreover, changes in information technologies, through their impact on total factor productivity and capital accumulation at both short and medium run horizons, have a strong, positive effect on GDP.[11]

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[7] See e.g., Geisler (2000). As he notes, fewer than twenty percent of patents ever result in commercialized products

[8] Participants at the 1998 NBER Macro annual meeting, including David Backus, Susanto Basu, and Russ Cooper, suggested that the weak relationship found may have been due to a mismatch between what is generally modeled as technology shocks and the shocks identified by patents and R&D. (See pp. 320-1 in the 1998 Macroeconomics Annual)

[9] See Alexopoulos and Cohen (2008) for some evidence about the lags between the discovery of a product and its commercialization.

[10] 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 provide an alternate explanation as to why my indicators produce stronger results.

[11] The finding that computer and telecommunication technologies are 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. See e.g. Wilson (2004).

The remainder of the paper is organized as follows. In section 2, I discuss the relationship between productivity and direct measures of technological change, describe the methodology and data used to create the indicators, and explore the new measures' properties. In section 3, I present results, based on a series of vector autoregressions (VARs), that describe the relationship between the book based indicators and GDP, productivity and inputs. Similar to the findings of Fisher (2003), CEV (2002, 2004) and ACEL (2003), mine support the predictions of the standard real business cycle model. Specifically, in response to a positive technology shock (defined as an increase in the orthogonal component of the technology indicator), real GDP, employment, total factor productivity and investment all increase after one year with the peak impact occurring 3-4 years following the shock.[12] However, consistent with other recent studies, I find that only a modest amount of the short run variation in employment can be attributed to technology shocks.[13] In section 4, I conclude and offer suggests for future research.

Section 2.

Direct measures of technological change

The most commonly used direct measures of technological change are those based on patent statistics, and more recently, patent citation statistics.[14] The attraction of these data, as Griliches (1990) notes, is understandable: they are available in fairly extended series (in the case of patents, all the way back to the industrial revolution), they are reasonably objective, they are linked to changes in society's technological know-how and appear to be related to inputs into the production of knowledge (such as research and development endeavors). In principle, then, they should be able to help us gain insight into the relationship between invention and innovation, on the one hand, and economic growth and productivity on the other.

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[12] These findings are in partial contrast to those presented in Gali (1999), Francis and Ramey (2005) and BFK (2006). 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 (2005) 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 (2006).

[13] Fisher (2003) finds, unlike others, that investment specific shocks have a very large impact on labor.

[14] See Griliches' (1990) survey article and Jaffe and Trajtenberg (2002) for good overviews of the patent literature, and Yorukoglu (2000) for an example of a work using the number of trademarks issued in the U.S. as a measure.

While patents and patent citations, contain a large amount of important information, they are subject to a number of debilitating shortcomings, especially for the purpose of identifying the effects of technological change in the short run, that is, at business cycle frequencies. First, there are usually long and variable lags between the development of a process or product and its appearance (if ever) on the market.[15] Second, patent fluctuations in the U.S. are on occasion the consequence not of more or less inventive activity but of changes in patent laws and/or the quantity of resources available to the U.S. patent office (See Griliches (1990)). For these reasons, studies that rely on patent statistics to measure technological change may yield misleading results - for example, that technology shocks do not have a significant impact on TFP or inputs.

Given the potential problems with patent data, one would prefer an indicator of technological change that is related to: (1) measures of knowledge production inputs, like research and development expenditures, and (2) 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. Specifically, indicators based on the publication of new books in the field of technology should reflect technological progress (at least some of which should be linked to R&D endeavors). Moreover, new books on technology (e.g., manuals) should be published when the idea or product is first commercialized (or is in the commercial pipeline) since books are costly to produce, and publishers want to introduce them as early as possible after the new product/process is commercialized to maximize the return on each new title.[16,17] As a result, the lag between the changes in technology captured by my book measures and changes in economic activity will be much shorter than those associated with the more traditional indicators.

Of course, it is possible that the number of new titles on technology may be related to trends in the publishing industry as a whole in the same way that patents can be affected by changes in patent laws. However, an added benefit of the new book based indicators is that series of new titles in other fields, such as

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[15] For example, while the first photocopier was developed and patented in the 1930s, the first photocopy machine became commercially available only in 1950.

[16] Although one might think that a significant lag exists between the appearance of a new title and the innovation to which it refers, when asked if this were the case, publishers responded in personal interviews that for technology books, the lags are minimal. They noted that technology changes rapidly and new titles must come to market quickly if profits are to be made from the publication. Most said that they can release a book on a major technological development within three months of its commercialization – with a six month average lag.

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

history or music, can be used as a control to determine if the results are driven by changes in the publishing industry or if they are indeed linked to the emergence of new technologies.

Creating the New Measures:

To create the new book based indicators, information of the following sort is required for each title: the type of book, the edition, the language of publication, and the country of origin. Specifically, I focus on the number of new English language titles (apart from new editions or reprints) in different fields of technology that are published in the U.S. each year, excluding books written on the history of a particular technology in the measures. 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 catalogues of new books titles by major subject fields used by American libraries to keep track of new publications available in the U.S. Each year from 1955-1997 the company reported the number of new titles by subject groups (e.g., Technology, Science, History, Home economics, etc) in their annual yearbook. For the earlier years, these estimates are based on information collected using surveys of the major book publishers in the U.S. Later they are based on information obtained from the Library of Congress's Cataloguing in Publication Program (CIP).[18] These records are of particular interest for my purpose since the titles released by major publishers are likely, first, to circulate more widely than those of smaller houses, and, second, to capture the major technological advances.

Bowker's estimates, referred to as the TECH series below, however, do suffer from three potential drawbacks. First, as noted, they omit books released by smaller publishers and thus may miss some innovations. Second, they do not include company manuals which are often an important source of information about new technologies. Third and most significant, books on computers are grouped with dictionaries and encyclopedias which makes it impossible to use Bowker's data alone to assess the impact of computer technologies.[19] To resolve these problems I also use the catalogue records from the Library of Congress to create broader indicators of total technical change (referred to as the TECH2 series), and ones that capture changes in information technologies (i.e., computer and telecommunications technologies).

[18] 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.

[19] 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.

The Library of Congress distributes database files in MARC21 format (See Appendix A for a sample of a Marc record and the corresponding database file). These files are used by the library to run their online title search, and by other libraries for cataloguing purposes. The main advantages to using information from the Library of Congress are, first, the immense size of its collection (since it is the copyright depository for the U.S., and one of the largest libraries in the world), and, second, that it can be used to create disaggregated indicators of technical change (e.g., ones focused on information technologies).[20] Each of the records contained in the databases - the Library's MARC21 records database (1968-1997) and the 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 a significant number of books imported from other countries.

The MARC21 records are in machine readable form, and record 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. The information in the first three fields allows me to identify new English language titles published in the U.S. 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).[21] For this paper, I focus primarily on books listed in the main subgroup T (which identifies the book as being in the field of Technology)[22], the subgroup of T that identifies traditional telecommunications technologies (TK5101-6720) and QA75-76 (which identifies books in Computer software and hardware). I then use the information contained in the records' subject and title fields to remove books from these groups that list history as a major topic since they are unlikely to help identify newly introduced technologies.

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[20] The Library of Congress' collections include more than 29 million books and other printed materials. The copyright law of 1870 required all copyright applicants to send two copies of their work to the library and the Copyright Act of 1978 established a mandatory deposit requirement within three months of publication for all works produced in the United States.

[21] See Appendix B for a listing of the major groupings and sub-groupings in T and Q. The Library of Congress Classification differs from the Dewey Decimal System Classification used to compile the Bowker's series. As a result, even if the type of new books considered by each institution were the same, the aggregate technology series would not be because of the differences in the classification systems.

[22] 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.

The indicators based on Bowker's records and the aggregate ones on technology and computer science drawn from the records of the Library of Congress are displayed in Figure 1. Two different series for computers are reported: COMP1 contains the number of new titles on computer software and hardware catalogued by the Library of Congress under QA75-76, and COMP2 includes the titles in COMP1 plus the new titles on computer networks catalogued under the T section. I also display in Figure 1 the Bowker's series for new titles in science (SCI) and history (HIS). I use the former to identify the relationship, if any, between scientific and technical advances, and the later to show that new history titles, as a proxy for other non-technical types of publications in general, do not share the same relationship with productivity and GDP that the technology series do.

A Measure of Diffusion?

When a company introduces a new technology, it often will release contemporaneously an instructional manual.[23] At roughly the same time, publishers, in an attempt to profit from the new technology, will introduce new titles to satisfy market demand.[24] It follows, then, that one should expect the majority of manuals/new book titles to precede diffusion of the new technology. Although it is impossible to show that this pattern holds for all technological advances, below I present some evidence to support the claim that the book indicators capture the moment of commercialization and do not simply track diffusion. Consider, for example, the timeline and graph for Computer hardware, shown in Figure 2A. The book measure identifies the period 1980-84 as a period of extremely rapid technological change in the computer field. In fact, this period does correspond with the first wave of personal computers (the IBM PC, the first IBM clones, the first Macintosh computer, and the first laptop) and the large jump in the power of computer processors.[25] However, an examination of data available from the Bureau of Economic Activity (BEA) on investment in computers and peripheries – the quintessential measure of the products' diffusion - reveals a very different pattern. For example, while the indicator shows a spike in innovation in the early 1980s there is no unusual

[23] For example, the MARC21 record displayed in Appendix A is the manual that was shipped with C++ when it was first introduced to the market. Moreover, although the healing properties of penicillin were discovered in the 1920s, books on penicillin did not appear in the Library of Congress until 1943 (the commercialization date) when the drug companies published treatment manuals for doctors. Indeed, 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.

[24] This timing was also confirmed in private conversations with a few major publishing houses.

[25] 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.

increase seen in hardware investment at this time, and the correlation between investment and the book series is less than 0.1. Although more suggestive than definitive, these data are consistent with the hypothesis that the indicators do not simply track diffusion.

In addition to this aggregate evidence, when appropriate data are available, new book indicators at a more disaggregate level can be used, along with information on sales of specific technologies, to determine the relationship between the diffusion of the technology and the corresponding indicator. 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 or less, it is possible to examine the relationship for products with a longer lifespan. Moreover, if the products in question have remained relatively unchanged over the time they are marketed, these case studies permit me to make a clear cut distinction between the timing of an innovation and its diffusion. Two such cases are presented in Figure 2B.[26] In the first panel, sales and publication data are shown for one of the most successful computers ever produced – the Commodore 64. It was first shipped in September 1982, and during its lifetime it is estimated that between 17 and 30 million machines were sold.[27] As the data presented in the graph illustrates, despite publishing time lags and modest changes in the computer over its lifespan, the figure clearly illustrates that the number of new titles peaks much earlier than yearly sales. In other words, the appearance of new titles tends to coincides with the date of the commercialization and clearly precedes the vast majority of sales (our measure of diffusion).

The second panel in Figure 2B reveals s a similar pattern for a very popular software product – Microsoft Windows 3.1. Windows 3.1, introduced in April 1992, was one of the most popular software programs during the years that it was in production. Available statistics suggest that more than 100 million copies of the product were sold by the time that Windows 95 was released 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.[28] Again, the graph confirms that the number of new titles peaks well in advance of the sales - in fact, the number of new titles hit its high during the first year the product was available.

[26] See Alexopoulos and Cohen (2008, 2009) for more case studies which demonstrate that the measures are more related to introduction of new technologies rather than the diffusion of the new technologies over the last century.

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

[28] The number of Windows programs licensed were obtained from Gartner Dataquest's historical Press Releases.

The evidence that new book titles appear during the early stage of a new technology's diffusion is also supported by evidence on the relationship between real investment data and the book series. Specifically, I examine this relationship by estimating the following bi-variate system:

$Z_t = \alpha + \delta t + BZ_{t-1} + \varepsilon_t$ where, $Z_t = [\ln(\text{Investment}_t), \ln(\text{Indicator}_t)]'$,[29] $B = \begin{bmatrix} \beta_{investment} & \beta_{indicator} \\ \gamma_{investment} & \gamma_{indicator} \end{bmatrix}$, α is a constant, and t represents a linear time trend. I run two regressions. In the first, I use aggregate investment in systems from the BEA with the total technology indicators (TECH and TECH2) and, in the second, I employ the BEA's investment series on information technologies in the regressions with the computer and telecommunications indicators (COMP, COMP2 and TEL) to capture diffusion of these goods. The ordering of the variables in the VAR is chosen to allow investment to have the largest possible impact on the book indicators in the short run. Table 1 reports the results. First, there is evidence that the new titles series have a positive and significant impact on investment. Second, it appears that the investment series does not Granger-cause the book series and the majority of point estimates suggest a negative – not a positive - relationship between the new titles and investment. This later set of results suggests that publishers release books before investment in the new technology peaks, that is, at the moment of commercialization not as the technology diffuses.[30]

The relationship between books, patents and R&D

If books on technology and computers are published when the new technology is commercialized, it would be reasonable to expect that R&D expenditures (an input into knowledge production) should serve as a leading indicator of the number of new technology titles. Of course, by the same logic, increases in scientific knowledge or patents should also lead to more books in the field of technology if the different measures are indeed capturing the same types of technological change and there is an endogenous component to technical change.

The question then is: do patents, science books[31], or R&D expenditures Granger-cause the number of new titles in technology?[32] The answer, based on the numbers reported in Table 2, it appears, is yes.[33] The

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[29] Although the results displayed are for the systems where the number of lags is chosen based on the Bayesian Information Criterion, similar findings emerge if the lags are instead chosen using the Akaike Information Criterion.

[30] These results are not significantly altered if the rate of change in investment is used instead of ln(investment).

[31] The Bowker's measure of new Science titles includes books published by major publishers in the U.S.

results are displayed for the number of lags selected by both the Bayesian Information Criteria (BIC) and the Akaike Information Criterion (AIC). They can be summarized as follows. There is little evidence of a relationship between patents and technology titles. However, when new titles in science are used as a measure of changes in scientific knowledge and R&D expenditures is used as a proxy for R&D intensity, I find evidence that both scientific advances and R&D Granger-cause new books in technology and computer science. Moreover, there is evidence of a feedback between technology and science since new technology titles often Granger-cause both R&D spending and new titles in Science.[34] In addition to their intrinsic interest, these results support the argument that new titles capture technological change - an output of inventive effort. The findings also support the predictions of endogenous growth models. However, even though there is a statistically significant relationship between the new technology indicators and R&D, the variance decompositions of the estimated bi-variate systems indicate that innovations in industrial R&D, while important, account for less than 30% of the variation of the new technology measures.[35]

Section 3.

In this section, I use my new indicators of technological change to explore three important issues. First, what is the impact of this type of technical change on GDP and productivity? Second, are the results affected by news about future technical advances as reflected in stock prices, and third, how do labor and capital inputs respond to a technology shock? The answers to these questions are of interest, first, because they may help us identify the role played by technology shocks in business cycle fluctuations and, second, because they are likely to help us select between competing business cycle models.

The economic data on GDP, capital, investment, labor hours, population and stock prices, are complied from the Global Insight's Basic Economics database (formally known as Citibase) and the BEA's national accounts database.[36] In addition, I use two measures for total factor productivity (TFP) – TFP1 is

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[32] 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.

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

[34] Interestingly, for the one case where technology Granger- causes patents, the results indicate that an increase in the number of new technology titles decreases the number of patents.

[35] This difference helps explain why the results presented in the following section indicate that the R&D measure does not generally have the same relationship with productivity measures, GDP and inputs as the new book-based indicators.

[36] A more detailed description of the variables used is provided in Appendix C.

calculated using the Tornqvist method, while TFP2, created by BFK (2006), cleanses the Solow residual by taking the aggregation issue seriously and attempting to correct for changes in utilization, imperfect competition and non-constant returns to scale. [37]

The relationship between GDP, productivity and the new title measures of technology

Figure 3 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.[38] Moreover, Table 3 reports the cross correlations of the data detrended with the band-pass filter suggested by Christiano and Fitzgerald (2003). Since technology may affect both the short run business cycle and the medium run cycle discussed by Comin and Gertler (2006), I report the two sets of cross correlations. The first set focuses on the higher frequency traditional business cycle movements (i.e., those frequencies between 2 and 8 years), while the second captures movements related to medium run cycles (containing frequencies between 2 and 30 years). The table reveals a few interesting patterns. First, the R&D variable often has a large positive correlation with GDP and productivity at one or two lags for the medium run frequencies. Second, in both cases the statistics confirm that there is a non-trivial positive correlation between lagged values of the new measures of technical change and current levels of GDP and productivity with the strongest of these related to the lagged computer and telecommunications technologies indicators. In contrast, lagged GDP and lagged productivity tend to be negatively correlated with the current levels of the new technology measures. These patterns are consistent with the type of Schumpeterian-style business cycle model presented in papers like Francois and Lloyd-Ellis (2006).

The Bi-variate Systems

To explore the extent of the relationship between the new measures, output and productivity, I estimate a series of bi-variate VARs where $Y_t = \alpha+\gamma t+\rho Y_{t-1} + \varepsilon_t$. In the first system $Y_t = [\ln(GDP_t), \ln(X_t)]'$, in

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[37] The Tornqvist Measure (TFP1) is based on statistics for the entire economy and assumes firms are perfectly competitive, but the elasticity of output with respect to capital and labor can vary over time. It is calculated as:
$TFP1_t = \Delta\ln(Y_t) - 0.5(\alpha_t + \alpha_{t-1})\Delta\ln(K_t) - (1-0.5(\alpha_t + \alpha_{t-1}))\Delta\ln L_t$ 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 hours worked. The elasticity of capital in time t and t-1, α_t and α_{t-1}, are computed using information on labor's share based on data in the NIPA. The BFK (2004) series used for TFP2 is their cleansed residual for the Non-Agriculture, Non-Mining Business Economy and ends in 1996.

[38] There are also changes in the number of new books prior to the growth slowdowns discussed by Zarnowitz (1992).

the second, $Y_t = [\ln(TFP_t), \ln(X_t)]'$, and in the third, $Y_t = [\ln(Y/L_t), \ln(X_t)]'$.[39] Here α is a constant, t represents a linear time trend, and X_t takes on the values of the new indicators, patents and industrial R&D and new titles in the field of history. Moreover, I assume a recursive ordering in which the technology shock at time t is defined as the component of the technology residual which is orthogonal to the contemporaneous GDP (or productivity) residual. This ensures that the technology shock only affects the variables of interest with a lag.[40] Based on the results of the Baysian Information Criterion a lag length of one was selected for each of the systems with the exception of the R&D where a lag length of 2 was chosen.[41] Overall, the results of these VARs will: (1) document the relationship between the new publication based indicators and the variables of interest, (2) determine how the results using the new measures differ from those using the traditional patent and R&D measures, and (3) demonstrate that the results are not simply driven by trends in the publishing industry.

GDP and Technology

The first two columns of Table 4 present the p-values for the Granger causality tests for the bi-variate systems focusing on GDP. The results indicate that the new technology indicators do significantly Granger-cause ln(GDP), but there is no significant evidence of reverse causation. The same relationships do not emerge using either the traditional measures of technical change - patents and R&D measures- or the new history titles. Specifically, patents appear to have virtually no relationship with ln(GDP), and there is only weak evidence that R&D has an impact on output. Moreover, it appears the results for the new technology indicators cannot be easily attributable to overall trends in the publishing industry. While both of the technology series and history series should be influenced by changes in the publishing industry, there is no evidence that the history titles Granger- cause ln(GDP).[42]

The first column of Table 5 displays the percent of variation in ln(GDP) due to the different technology variables at 3, 6 and 9 year horizons. Three results are worth highlighting. First, the percent of

[39] Since the unit root tests are inconclusive, I opt to use levels instead of first differences and include a time trend.

[40] 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 are sensitive to the ordering..

[41] For most cases, the Baysian and Akaike Criteria selected the same lag length. Since the results are virtually identical, I only report the results based on the BIC selection.

[42] 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 economic activity, and (2) would be affected by changes in the publishing industry.

variation in ln(GDP) due to technology at a 3 year horizon is approximately 10-20 percent, 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 in the short run. Third, the new indicators are better able to explain the variation in GDP than the more traditional indicators (i.e., patents and R&D expenditures).[43] Indeed, the computer technology indicators may account for as much as 49 percent at a nine year horizon, while R&D or patents only account for about 4 percent. These results are consistent with the statistics presented in Table 6 where I report the incremental change in R^2 from adding the technology variables. Again, it appears that the largest gain comes from adding the information technology measures.

Figure 4 displays the impulse responses of GDP to a one standard deviation technology shock for each of the indicators used along with 1.65 Monte Carlo standard error bands, as well as the impulse response to a one standard deviation history titles shock. The figure illustrates that GDP rises in response to a positive technology shock identified by the new measures with the peak response occurring after 2-4 years.[44] Moreover, at the peak, a one-standard deviation shock results in a 0.008% - 0.014% increase in GDP.[45] In contrast, there is no significant response of output to the shocks identified by the patents or R&D or to the shock related to the new history titles.

Productivity and the new measures

I turn now to the relationship between my new indicators and productivity. If, as I have argued, these indicators measure technological advance, a positive and significant relationship should exist between the indicators and productivity. In Tables 4-6, I report the results of the bi-variate VARs using three different productivity measures – Y/L (output per worker), TFP1(the Tornqvist Measure) and TFP2 (the corrected Solow residual created by BFK (2006)).

Five notable findings can be discerned from the p-values of the Granger causality tests reported in Table 4. First, the new measures, with the exception of TECH2 (all LoC new technology books), tend to Granger- cause the productivity measures. Second, the TECH series (Bowker's new technology books) has a stronger relationship with the productivity measures than the TECH2 series which may be an indication that

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[43] The results reported in Table 5 are similar to those from tri-variate VARs including GDP, the technology indicator, and a measure of consumption or investment.

[44] These results are generally unaffected by the inclusion of other shocks such as monetary policy shocks, oil shocks, and fiscal policy shocks.

[45] In other words, a shock causing a 1% increase in the various types of technology titles causes GDP to increase by between 0.048% and 0.16% at the peak of the response.

the series based on titles release by major publishers capture more important or widely adopted new technologies than the broadly based series created from the Library of Congress' collection. Third, similar to the findings for output, the strongest statistical relationships are obtained using the indicators related to information technologies. Fourth, while there is evidence that R&D may Granger- cause the productivity measures (and vice versa), I find no significant relationship between patents or history titles and the productivity measures.[46] Fifth, the productivity measures do not appear to Granger-cause the computer indicators or the TECH series, but do Granger-cause R&D, TECH2 and TEL series.

Table 5 displays the variance decompositions for the productivity VARs alongside those from the bi-variate GDP VARs, and Table 6 reports the incremental change in R^2 from adding the technology variables. Again, it appears that computer indicators are able to explain a significant portion of the variation in productivity at both the three year horizon (7.5-16.5 percent) and at the nine year horizon (19-42 percent). The traditional telecommunications technologies, and those captured by TECH, also appear to explain a non-trivial portion of TFP1 variation. In contrast, the patent series explains less than 2.5 percent of the variation in any of the productivity measures at the nine year horizon. R&D, on the other hand, may be able to explain a significant percent of the variation of TFP2, but only at medium run horizons.

The impulse responses of the productivity measures to the various one-standard deviation technology shocks are depicted in Figure 5. 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 differences in the sizes and significance of the responses across the measures. Specifically, the responses to computer and telecommunications technology shocks are significant for all the productivity measures at the 10 percent level, while only TFP1 and output per hour significantly respond to a TECH shock. Overall, for cases where the response is significant, a one-standard deviation shock appears to increase TFP1, TFP2 and Y/L at the peak of its response by between 0.003 % - 0.006%, 0.004% - 0.007%, and 0.003% - 0.004% re-

[46] These results echo the ones Shea found using use and manufacturing patents from 1959-1991 in his 1998 paper. However, Christensen (2008) is able to find a positive relationship between patents and TFP for some (but not all) specifications she examines for the period 1948-2002. While she finds a statistically significant positive relationship when no deterministic trend is included in the VAR or when she allows for a trend break in 1973, I find that results based on a VAR with the trend removed or a VAR that allows for a trend break in 1973 still do not uncover a positive statistical relationship between TFP and patents for the period I examine.

spectively.[47] Moreover, the timing of the peak responses also differs with the response to a telecommunications shock peaking at year 1 and the responses to other technology shocks peaking around year 3.

News Shocks?

In a recent article, Beaudry and Portier (2006) use stock price data to identify 'news shocks'. These, they maintain, capture information about future technical progress and may, therefore, account for a large portion of business cycle fluctuations. Since new technology titles may provide news about the commercial availability of new innovations, it is natural to wonder, first, if a relationship exists between the new indicators and these stock prices and, second, if the results presented above are sensitive to the inclusion of these news shocks? To answer these questions, I estimate a series of VARs including the stock price variable used in Beaudry and Portier (2006). The results presented in Tables 7 and 8 are based on the following system:

$Y_t = \alpha+\gamma t+\rho Y_{t-1} +\varepsilon_t$. In the first case, $Y_t = [\ln(BP_t), \ln(GDP_t), \ln(X_t)]'$, in the second case, $Y_t = [\ln(BP_t), \ln(TFP_t), \ln(X_t)]'$ and in the third case $Y_t = [\ln(BP_t), \ln(Y/L_t), \ln(X_t)]'$. Here, following Beaudry and Portier (2006), ln(BP) is defined as the log of the per capita value of the annual Standards & Poors 500 Composite Stock Prices Index deflated by the GDP deflator, and X_t takes on the values of the new indicators, patents and industrial R&D and new titles in the field of history.

Although Beaudry and Portier (2006) identify the news shock as the ones that effect TFP with a lag, I place the stock market variable first in the ordering for two reasons. First, Beaudry and Portier's (2006) findings suggest that, even though the shock may not have an impact on TFP within a quarter, the shock does have a significant impact on TFP within the first year. Since I am using annual data, this ordering is consistent with their findings. Second, by placing the stock variable first, I allow it to have the maximum influence on the other variables in the system.

The p-values reported in Table 7 indicate that, at least in the short run, GDP and the productivity variables are still significantly influenced by the technology variables, while the technology measures are still not significantly affected by GDP or productivity in the short run.[48] Moreover, as Table 8 demonstrates, the percent of variation in GDP and the productivity measures that can be attributed to the new technology

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[47] This amounts to a peak increase of 0.023%-0.05% in TFP1, 0.023%-0.026% in TFP2 and 0.017 % - 0.03% in Y/L following a 1% increase in the various technology measures.

[48] The table also indicates that patents granger-cause GDP at a 1% level and almost Granger-cause TFP1 at a 10% level when the news variable is included. However, the coefficients for the patent variables in these cases are negative suggesting that increases in patents decrease GDP and TFP1 in the short-run. This negative relationship between patent shocks and TFP also emerges in Shea's (1998) study.

measures do not significantly differ from the results displayed in Table 5, even though the percent of variation in the variables attributable to the stock price variable (BP) is substantial. Finally, Figure 6 confirms that GDP and the productivity measures all increase in response to the technology shocks identified by my new indicators.

Direct measures of technology and the components of GDP

The final question I attempt to answer using my new indicators is the following. What impact does a technology shock – based on these indicators – have on labor input? As it happens, this is a hotly contested issue among macroeconomists: in the standard New Keynesian model, labor input initially declines, in the standard neo-classical real business cycle model, it increases. An answer to the question may, therefore, help us discriminate between the two. To address the question, I expand the number of variables in the VAR to include investment, labor and TFP. Specifically, I assume that $Y_t = \alpha+\gamma t+\rho Y_{t-1} +\varepsilon_t$ where $Y_t = [\ln(Inv_t), \Delta\ln(N_t), \ln(TFP_t), \ln(X_t)]'$, t is a linear time trend, and X_t represents the technology indicators. Again, I place the technology measures last in the ordering on the assumption that shocks to this variable only affect productivity, hours and investment with a lag.

In Table 9 I report the percent of variation due to technology in the four variable VARs using the different productivity measures. As can be seen, only a small percent of variation in hours is attributable to the type of technology captured by the new measures. Instead, the majority of the GDP fluctuations are linked to the impact of changing technologies on TFP with the computer technologies (measured by COMP1 and COMP2), once again, explaining the highest percent of variation in productivity.[49]

Finally, a comparison of the estimated impulse responses to those from a standard real business cycle model and a standard sticky price model can aid in model selection. As Gali (1999) points out, the standard real business cycle model predicts an increase in hours following a positive technology shock, while the standard sticky price model yields a decrease. Figures 7 and 8 display the estimated impulse response functions for the new technology indicators, investment, labor and the different measures of TFP. They show that a positive technology shock increases TFP, investment and hours growth one period after the shock with a peak response usually occurring two-four periods after the shock. The increase in TFP is generally significant for approximately 4-5 years following a shock to computer or telecommunications technologies. In contrast,

[49] The percent of variation that can be attributed to the new computer measures is higher for the case where investment in information technology is used instead of the total investment series. These results are available from the author upon request.

the increase in the growth of labor and/or investment tends to become statistically significant with a lag. While I cannot rule out a weak negative response of labor in the very short run due to the annual nature of the indicators, the positive response of hours growth indicated by the point estimates is more consistent with the responses predicted by a standard real business cycle model.

Conclusion

Although many of us believe that technical change plays an integral role in both economic growth and business cycle fluctuations, the lack of good measures of technical change has placed limits on the types of analysis we can perform. The work I present in this paper therefore contributes to the literature in a number of ways. The first contribution is through the creation of a new measure of technological change employing previously unutilized information on new book titles in the field of technology from R.R. Bowker and the Library of Congress. These new annual indicators sidestep many of the shortcomings associated with the traditional measures (such as patents). They are objectively determined, they coincide with the date that new products/processes hit the market, and are positively related to inputs into knowledge production (such as scientific advances and R&D).

The others relate to the creation and evaluate of business cycle models. First, my results suggest that more attention needs to be paid to the effect of technology on medium run cycles and on models that capture the links between R&D effort and the commercialization of new technologies. Second, the findings speak to an ongoing debate among business cycle theorists – What impact do technology shocks have on the economy?. Since many of these models assume that these shocks play a large role in economic fluctuations, an ability to identify their effect on output, productivity, and employment is of obvious value. Specifically, an answer to this question will help us determine: (1) the extent to which pure technology shocks are a source of business cycle fluctuations, and (2) which of the two competing models of economic fluctuations, the sticky price or the standard real business cycle one is more consistent with the data. I address these issues by utilizing my new measures in a series of vector autoregressions. The results indicate first, that these measures in general are better able to explain movements in TFP, investment and labor than either patents or R&D expenditures, and, second, that computer technologies have the greatest impact on these variable. Consistent with the predictions of both real business cycle and sticky price models with accommodating monetary policy, I find that, in response to a positive technology shock, GDP, TFP, investment and hours increase.

It may appear that the positive, even if weak, relationship between technological change and labor reported in this paper is out of step with recent findings of, for example Gali and Gambetti (2008), that the sign of the unconditional correlation of labor productivity and hours post-1984 has shifted from positive to negative. Appearances, however, in this instance are deceiving. In particular, as the two authors point out, a large component of the change is attributable to a fall in the correlation conditional on the *non-technology* as opposed to *technology* shocks while the correlation conditional on investment-specific technology shocks (those most closely related to the ones picked up by my new measures) overall remain positive, if small.

Overall, this new approach to measuring innovative activity and the results derived with them are likely to prove useful in a variety of technology related research areas. For example, because it is possible to create book-based measures for many countries, these new indicators should facilitate cross-country comparisons of technological innovation. Moreover, because it is possible to create linkages between inputs into the inventive process and outputs of new technology, it should also be possible to use these measures to examine the factors that determine the international diffusion of new techniques. Finally, because these measures permit a relatively fine-grained breakdown of new technologies by sector and by type of innovation, we may be able to develop more precise indicators of process and product technologies. Since there is reason to believe, on the basis of some findings in the industrial organization literature (e.g., Ross and Zimmerman (1993)) that process driven advances are linked to short-term decreases in labor inputs, this may help us make sense of the apparent negative relationship between hours worked and labor productivity or, more generally, jobless recoveries.

References:

Alexopoulos, Michelle and Jon Cohen. 2008. "Volumes of Evidence: Examining Technical Change Last Century through a New Lens", Working paper, University of Toronto

Alexopoulos, Michelle and Jon Cohen. 2009. "Measuring our ignorance, one book at a time: New indicators of technological change, 1909-1949," *Journal of Monetary Economics* 56(4): 450-470.

Altig, D., Christiano, L., Eichenbaum, M. and J. Linde, 2003. "Technology Shocks and Aggregate Fluctuations." Manuscript, Northwestern University.

Basu, S., J. Fernald, and M. Kimball, 2006. "Are Technology Improvements Contractionary?" *American Economic Review* 96(5):1418-1448.

Beaudry, P., and F. Portier, 2006. "Stock Prices, News and Economic Fluctuations," *American Economic Review*, 96(4): 1293–1307.

The Bowker Annual, R.R. Bowker Company, New York, Various Years.

Christensen, L. E., 2008. "Do Technology Shocks lead to Productivity Slowdowns? Evidence from Patent Data." IMF working paper 08/24.

Christiano, L., M. Eichenbaum and R. Vigfusson. 2002. "What Happens After a Technology Shock?", Manuscript, Northwestern University

Christiano, L., M. Eichenbaum and R. Vigfusson. 2004. "The Response of Hours to a Technology Shock: Evidence Based on Direct Measures of Technology." National Bureau of Economic Research, Inc, NBER Working Papers: 10254

Christiano L., and T. Fitzgerald. 2003. "The Band Pass Filter," *International Economic Review*, 44(2): 435-465

Comin, Diego and Mark Gertler, 2006. "Medium-Term Business Cycles," *American Economic Review*, 96(3): 523-551.

Jaffe, A. 1998. "Discussion of *What Do Technology Shocks Do*?" *NBER Macroeconomics Annual 1998*, 13: 317-20.

Jaffe, A and M. Trajtenberg . 2002 "Patents, Citations and Innovations: A Window on the Knowledge Economy." Cambridge : MIT Press.

Jorgenson, D. 2001."Information Technology and the U.S. Economy", *American Economic Review*, 91(1):1-32.

Fisher, J. "Technology Shocks Matter." Working Paper, Federal Reserve Bank of Chicago, 2003-06-01

Francis, N. and V. Ramey, 2005. "Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited," *Journal of Monetary Economics*, 52(8): 1379-1399.

Francois, P. and Huw Lloyd-Ellis, 2006. "Intrinsic Business Cycles with Pro-Cyclical R&D," Working Paper 1102, Queen's University, Department of Economics

Gali, Jordi, 1999. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *American Economic Review* 89: 249-271.

Gali, Jordi, 1998. "Discussion of What Do Technology Shocks Do?" NBER Macroeconomics Annual 1998, 13: 310-17.

Gali, Jordi and L. Gambetti. 2008. "On the sources of the Great Moderation," NBER Working Paper 14171.

Gali, Jordi and P. Rabanal, 2004."Technology Shocks and Aggregate Fluctuations: How Well Does the RBS Model Fit Postwar U.S. Data?" NBER Working Paper 10636

Geisler E., 2000."The metrics of science and technology." Westport, Conn.: Quorum Books

Griliches, Z. 1990 "Patent Statistics as Economic Indicators: A Survey." *Journal of Economic Literature* 28 (December): 1661-1708.

Library of Congress Classification. A-Z, Library of Congress, Cataloguing Distribution Services, Washington, D.C. Various years

Oliner, S. and D. Sichel, 1994 "Computers and Output Growth Revisited: How Big is the Puzzle?" *Brookings Papers on Economic Activity* 1994(2): 273-317.

Reimer, J. 2005. "Total share: 30 years of personal computer market share figures", Ars Technica, Wednesday, December 14.

Ross, D. and K. F. Zimmermann 1993. "Evaluating reported determinants of labor demand", Labour Economics 1(1): 71-84.

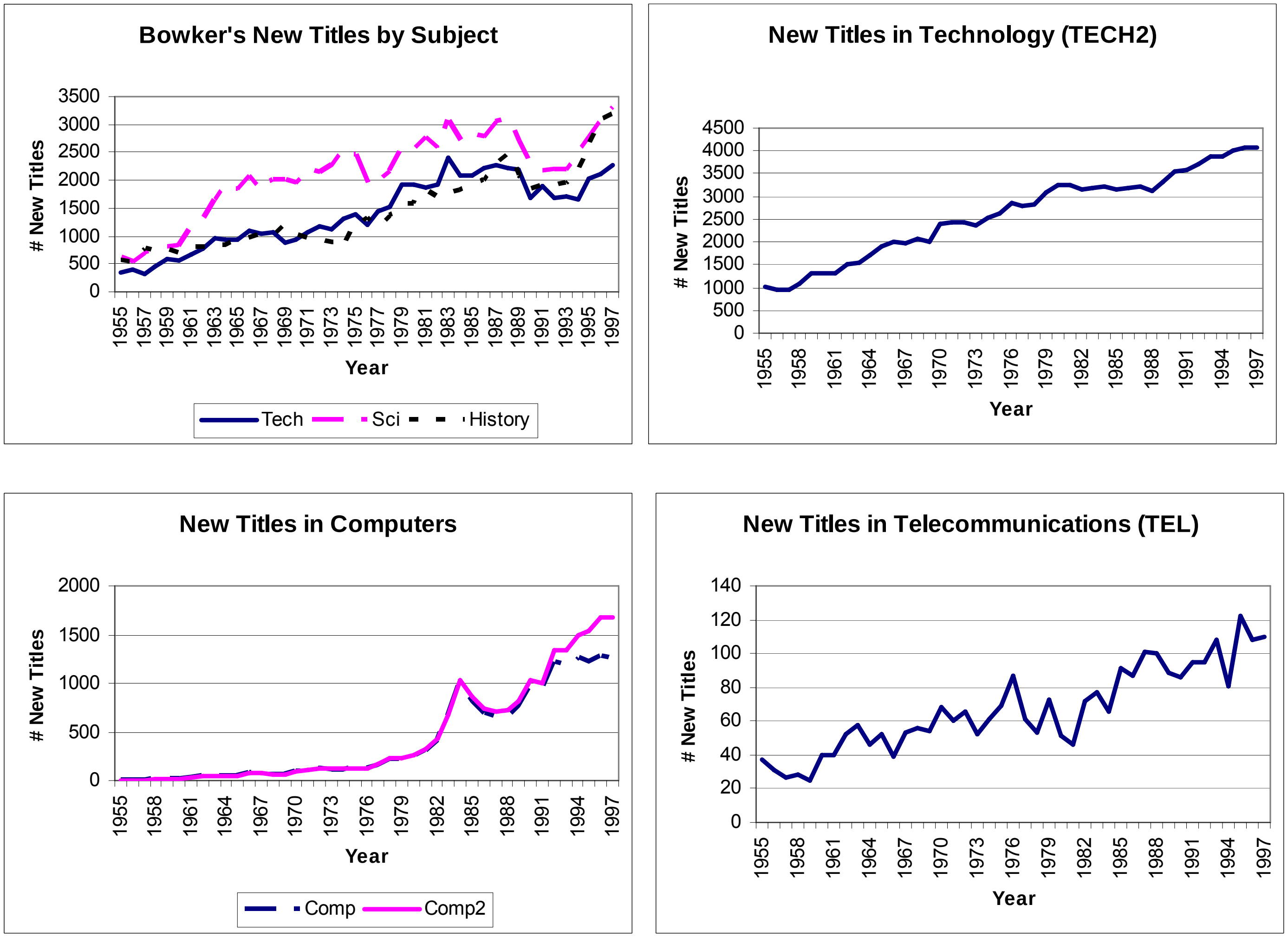
Shea, John. 1998. "What Do Technology Shocks Do?" *NBER Macroeconomics Annual 1998,* 13: 275-310.

Wilson, D. 2004. "IT and Beyond: The Contribution of Heterogeneous Capital to Productivity" Manuscript Federal Reserve Bank of San Francisco,

Yorukoglu, M. 2000. "Product vs. Process Innovations and Economic Fluctuations" Carnegie-Rochester Conference Series on Public Policy, 52(0):137-63.

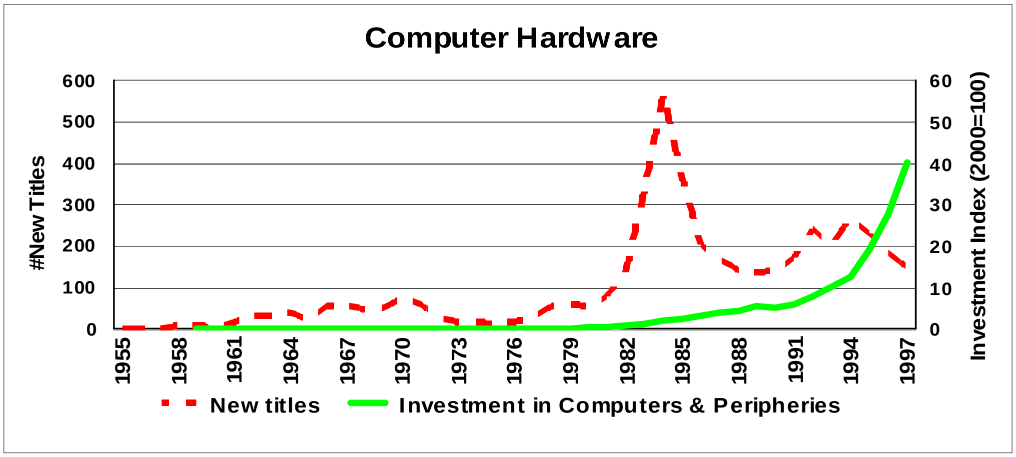
Zarnowitz, V. 1992. "Business cycles: Theory, history, indicators, and forecasting", NBER Studies in Business Cycles, vol. 27. Chicago and London: University of Chicago Press

Figure 1. The Indicators



Sources: R.R. Bowker's The Book publishing annual (various years), the Library of Congress' MARC21 files and the Thompson Dialog Remarc Database.

Figure 2A. New Hardware Titles, Investment and Timeline

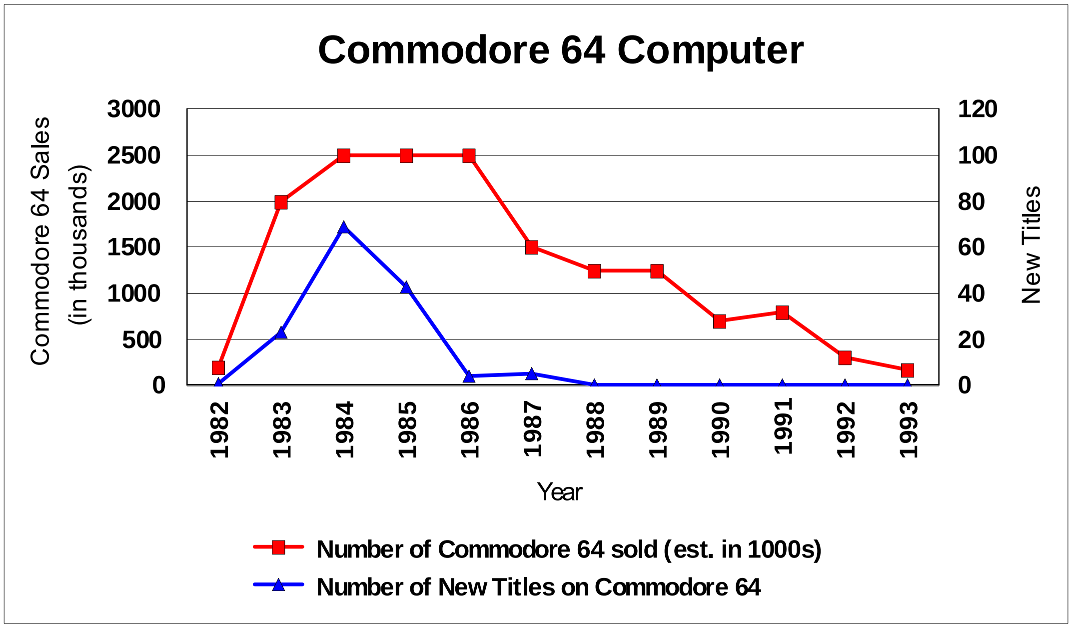


Sources: The investment series is downloadable from the Bureau of Economic Analysis, and the new titles series is based on titles recorded in the Library of Congress' MARC21 files and the Thompson Dialog Remarc Database.

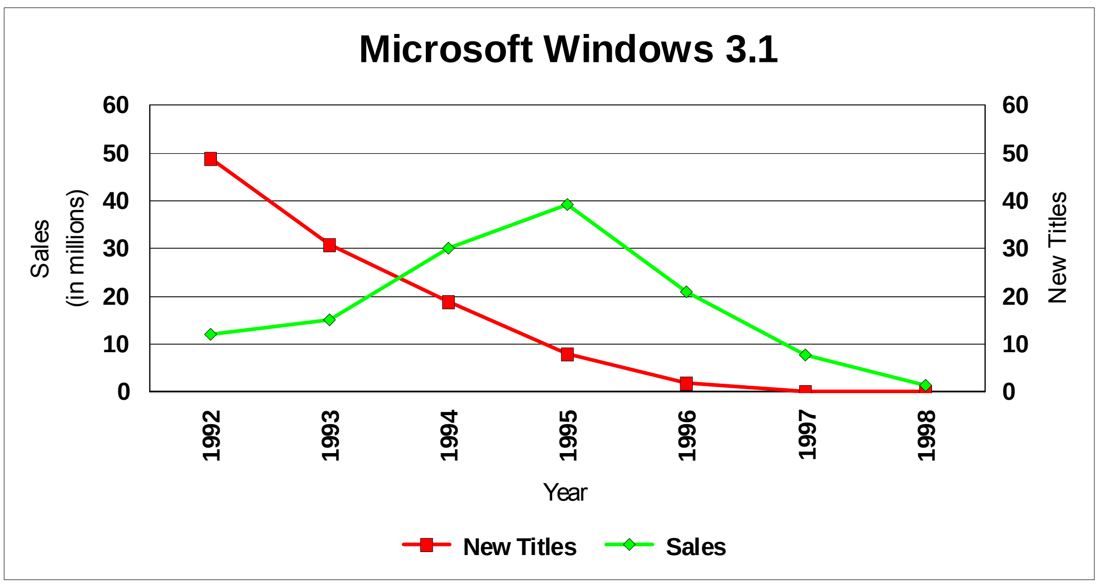
Timeline with Major dates

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 key-board 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, commo-dore introduces AMIGA and Intel ships 80286 chips
1985	Intel 80386 chip introduced
1986	First computer using new 80386 chip sold
1988	Next cube 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 2B.

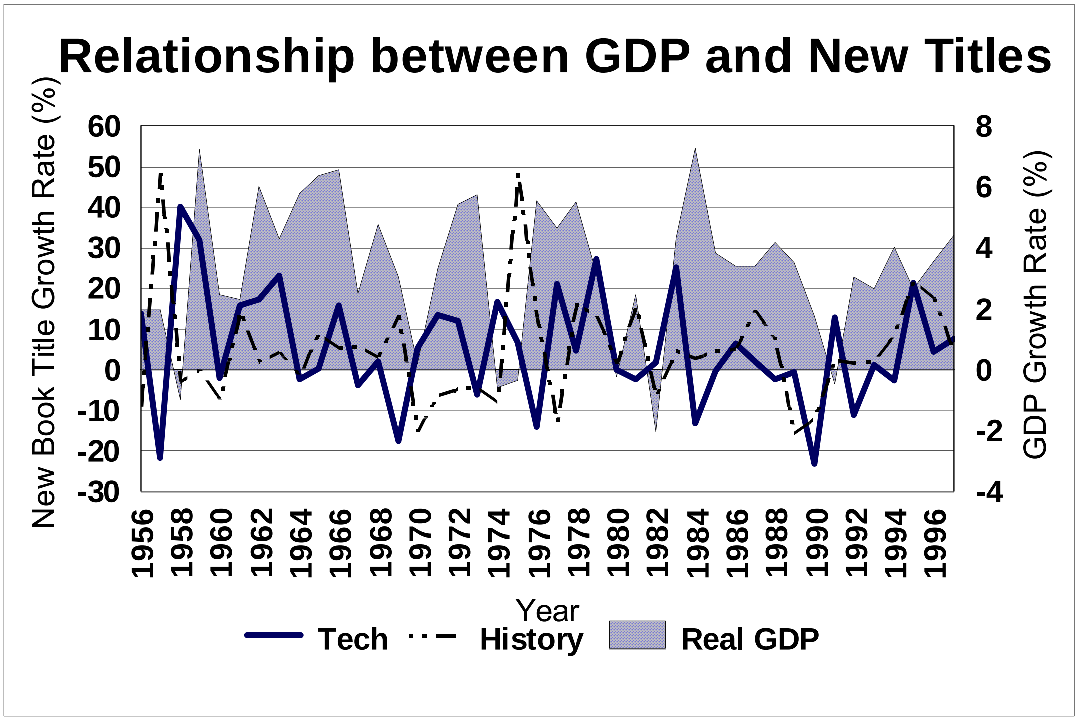


Notes: The commodore 64 was not available until September of 1982. The number of new titles is based on the Library of Congress' MARC21 files and the sales data is from Reimer (2005)



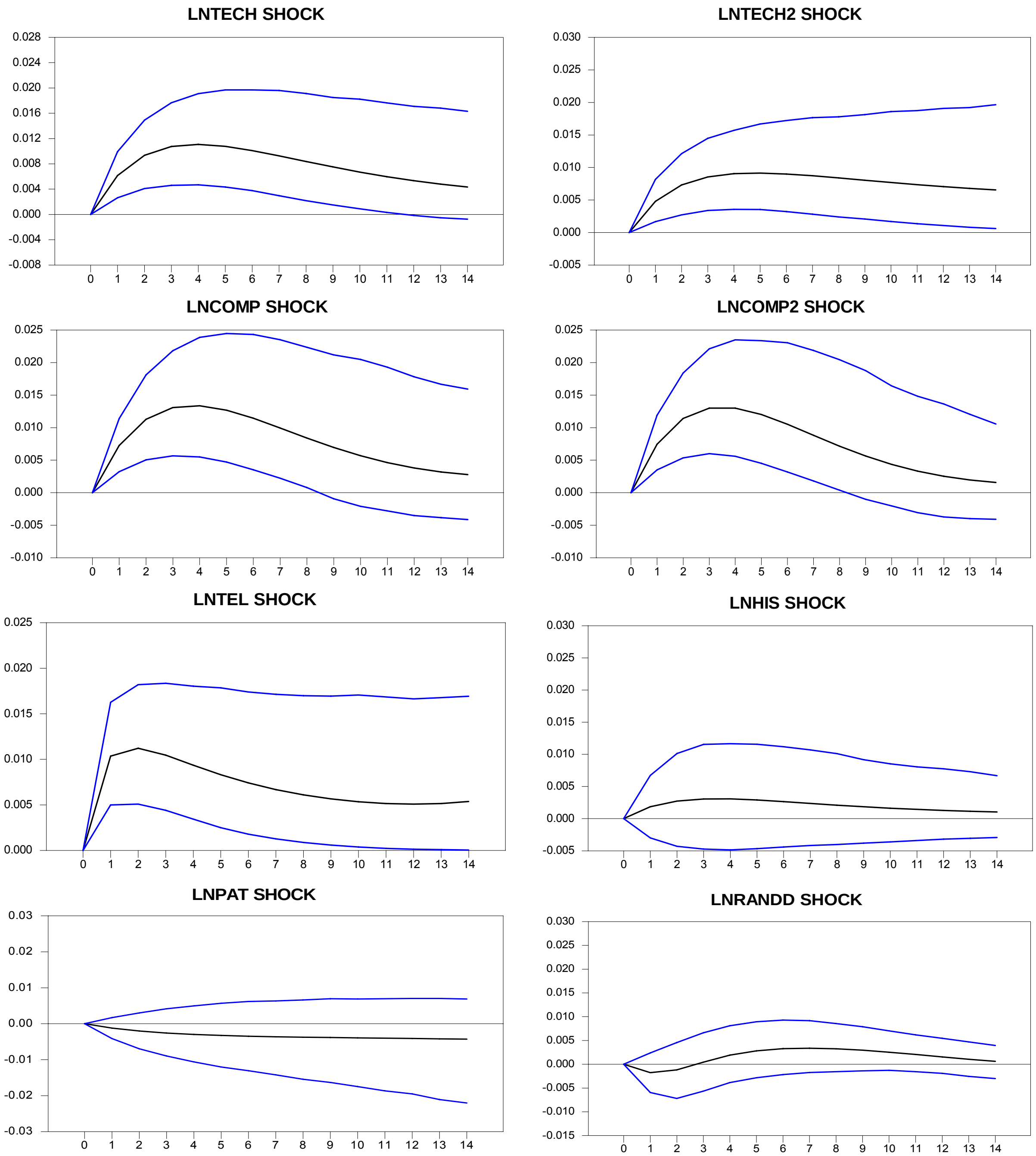
Notes: The number of new titles is based on the Library of Congress' MARC21 files and the sales data is obtainable from Gartner Dataquest

Figure 3.



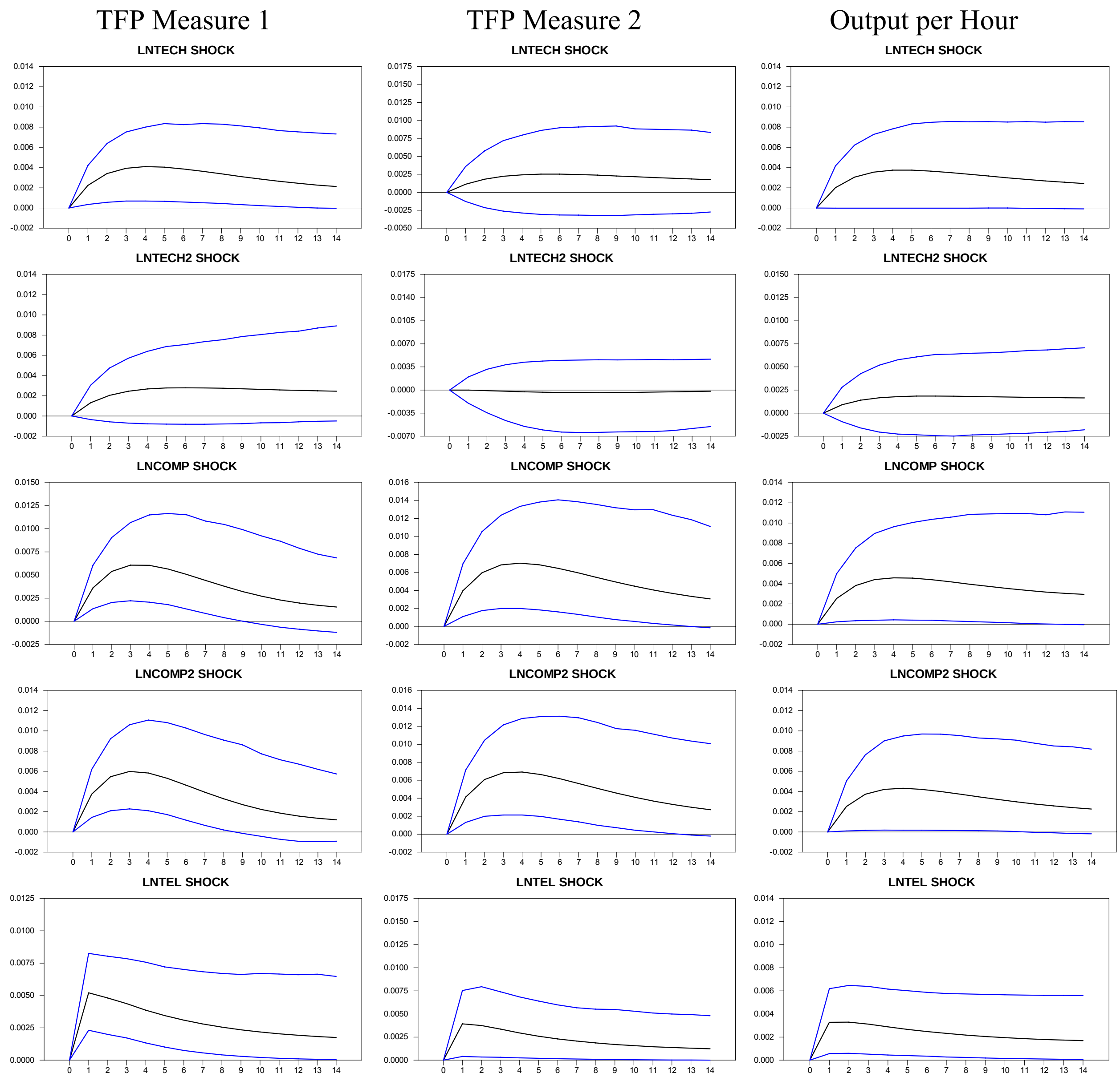
Sources: The real GDP series is obtainable from the BEA. The Tech and History series are based on statistics reported in R.R. Bowker's The Book publishing annual (various years)

Figure 4. Impulse Responses of ln(GDP) to Positive Technology Shocks



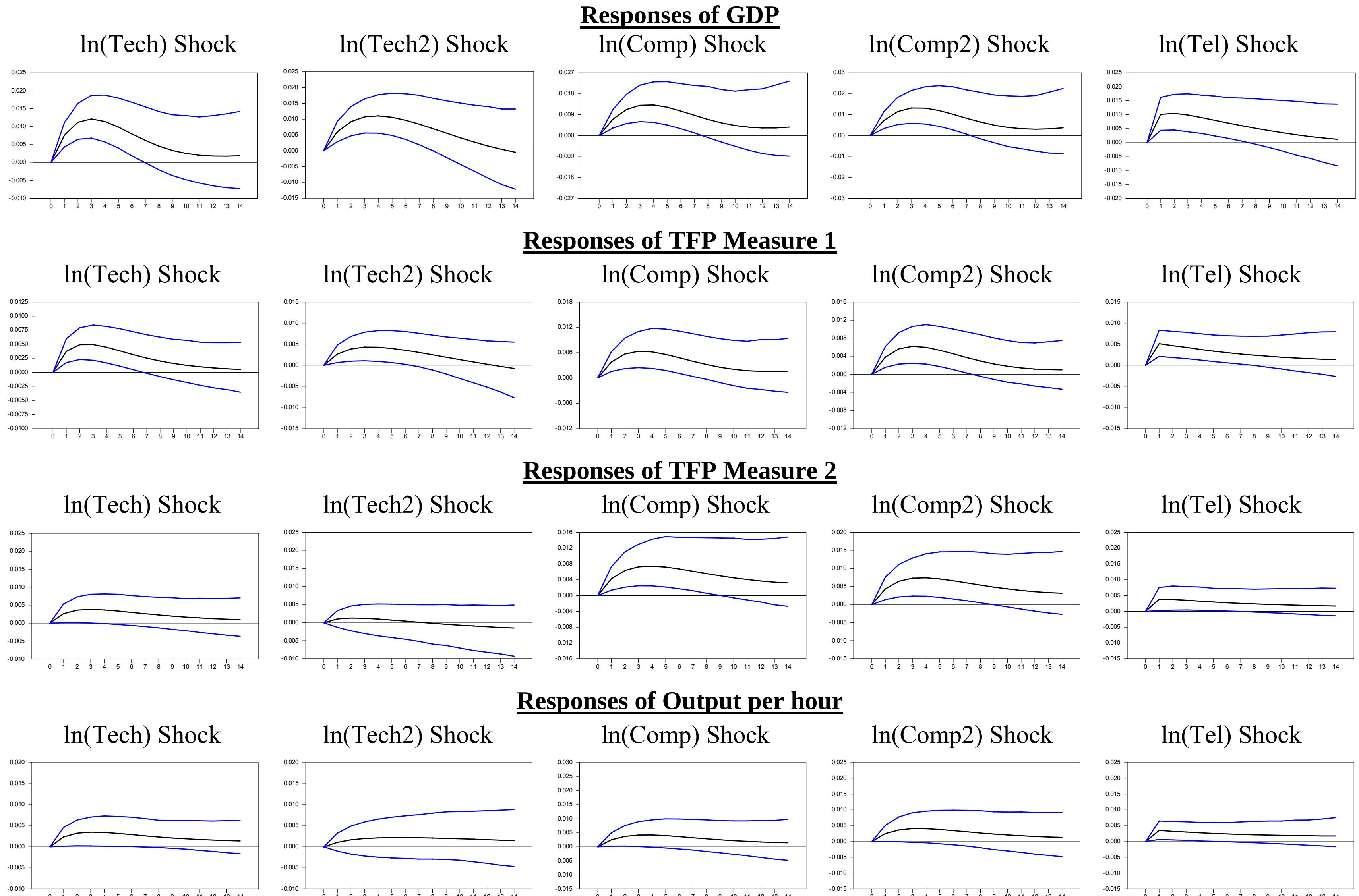
Notes: These VAR Cholesky orthogonalized impulse response functions are estimated using annual data from 1955-1997. Each panel displays the response, in percentages, to a one-standard deviation shock to technology (or history titles) and the 90% confidence interval. In each case, ln(GDP) is the first variable in the bi-variate system.

Figure 5. Responses of Productivity Measures to Positive Technology Shocks



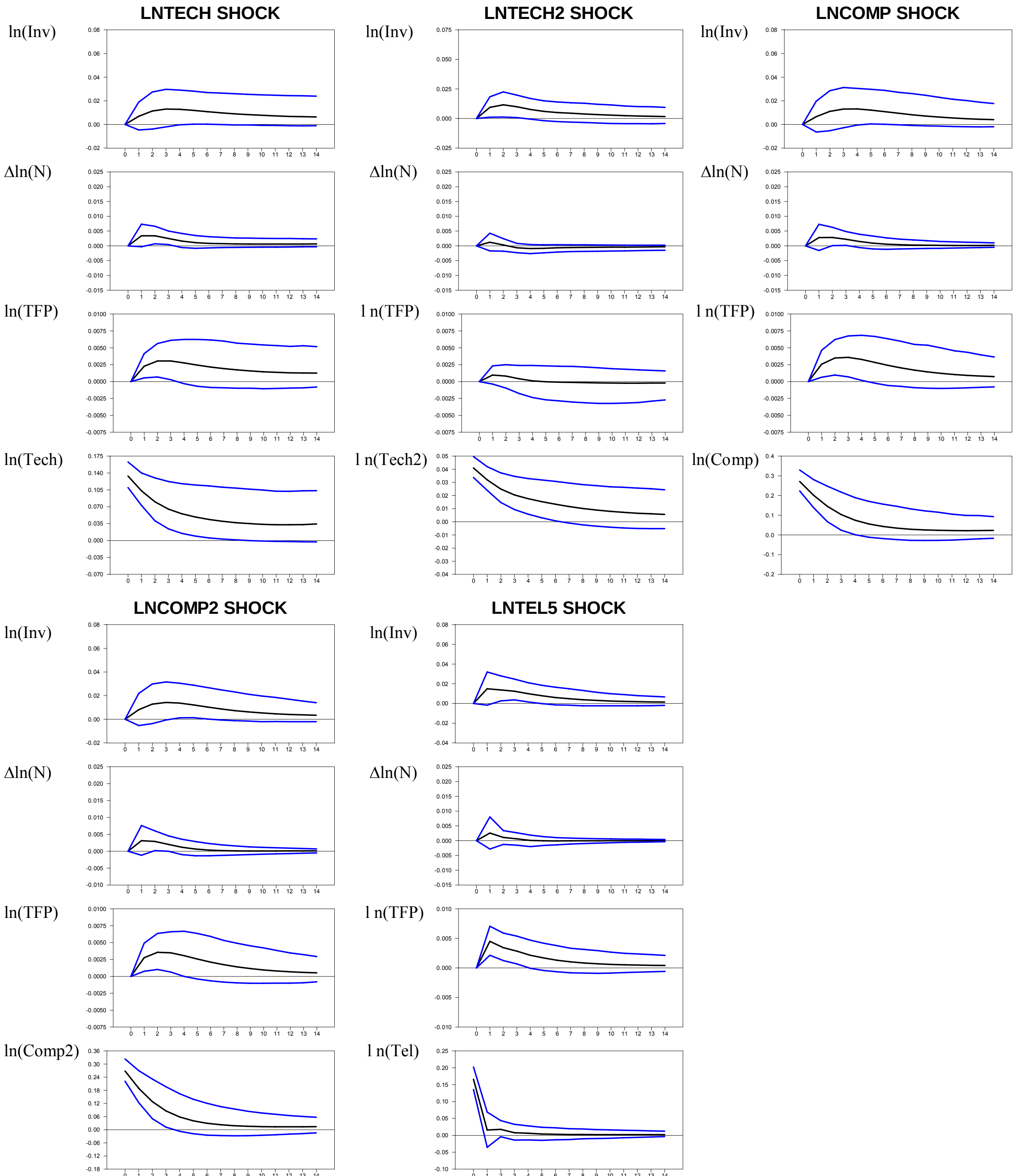
Notes: These VAR Cholesky orthogonalized impulse response functions are estimated using annual data from 1955-1997. Each panel displays the response, in percentages, to a one-standard deviation shock to technology and the 90% confidence interval. In each case, ln(TFP) or ln(Y/L) is the first variable in the bi-variate system.

Figure 6. Responses of GDP and Productivity to Technology Shocks (Tri-Variate VAR)



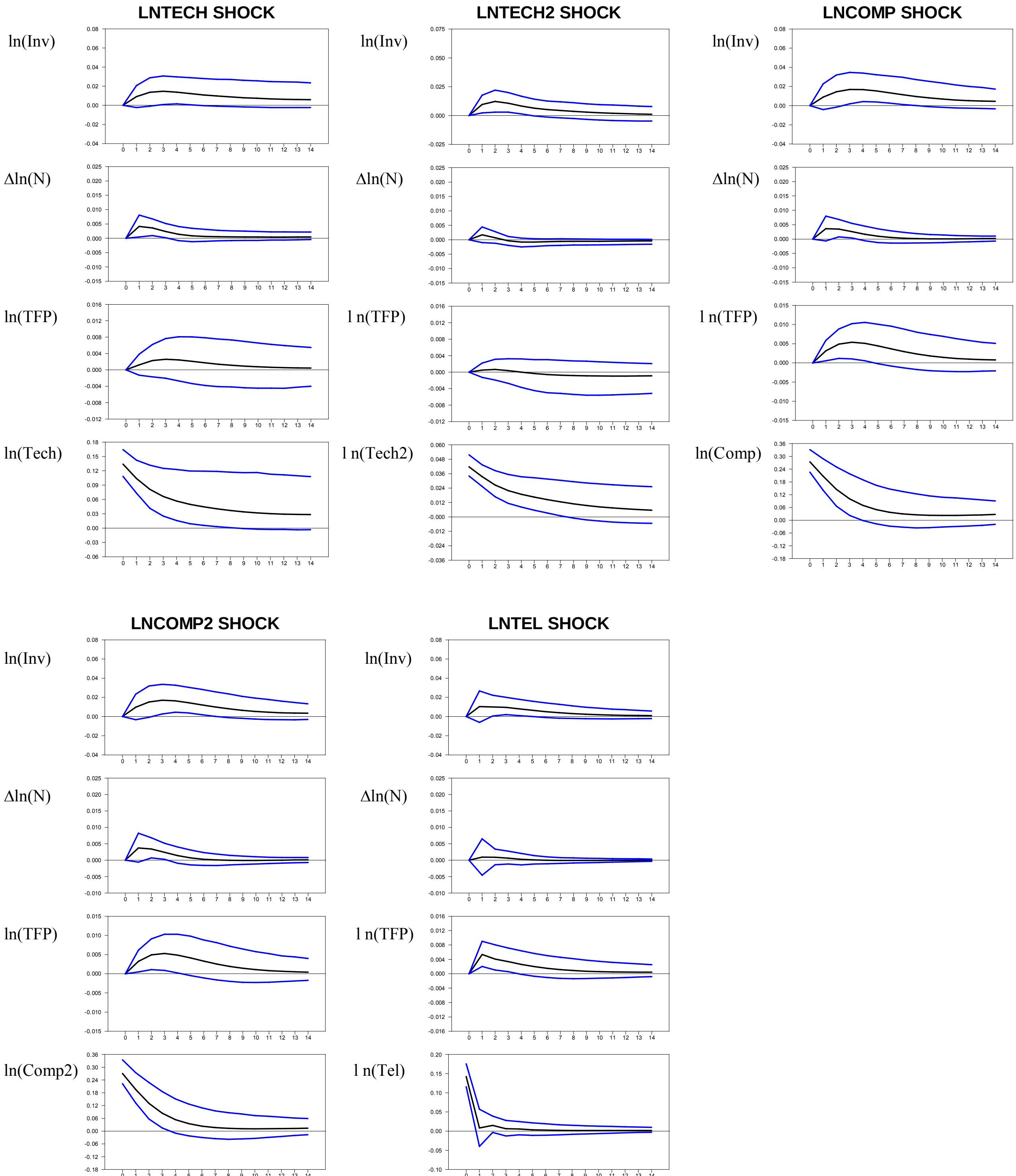
Notes:. Each panel displays the response, in percentages, to a one-standard deviation shock to technology and the 90% confidence interval. In each case, ln(BP) is ordered first, and ln(technology) is ordered last in the VAR. The results are based on annual data from 1955-1997.

Figure 7. Impulse Response Functions for Four Variable VAR using TFP Measure 1



Notes: These VAR Cholesky orthogonalized impulse response functions are estimated using annual data from 1955-1997. Each panel displays the response, in percentages, to a one-standard deviation shock to technology and the 90% confidence interval. In each case, $Y_t = \alpha+\gamma t+\rho Y_{t-1} + \varepsilon_t$, where $Y_t = [\ln(Inv_t), \Delta\ln(L), \ln(TFP1_t), \ln(X_t)]'$, and X_t is the value of the indicator at time t.

Figure 8. Impulse Response Functions for Four Variable VAR using TFP Measure 2



Notes: These VAR Cholesky orthogonalized impulse response functions are estimated using annual data from 1955-1997. Each panel displays the response, in percentages, to a one-standard deviation shock to technology and the 90% confidence interval. In each case, $Y_t = \alpha + \gamma t + \rho Y_{t-1} + \varepsilon_t$, where $Y_t = [\ln(Inv_t), \Delta\ln(L), \ln(TFP2_t), \ln(X_t)]'$, and X_t is the value of the indicator at time t.

Table 1: The Relationship between Investment and the Indicators

Panel A: Dependent Variable : Investment

Technology Indicator	$\beta_{investment}$	$\beta_{indicator}$	Does the Indicator Granger-Cause Investment? P-Value	Variance Decomposition (effect of Indicator) 3 yr	6 yr	9 yr
Bowker's Tech	0.6026***	0.0756**	0.036	4.88	12.57	15.98
LOC Tech	0.5614***	0.1829***	0.002	6.14	18.79	25.58
Computers	0.7573***	0.0424*	0.086	5.79	16.06	20.79
Comp+networks	0.7632***	0.0474*	0.057	6.84	17.51	21.61
Telecomm	0.7758***	0.0397	0.364	1.18	1.73	1.82

Panel B: Dependent Variable Technology indicator

Technology Indicator	$\gamma_{investment}$	$\gamma_{indictor}$	Does Investment Granger-Cause the Indicator? P-Value	Variance Decomposition (effect of Investment) 3 yr	6 yr	9 yr
Bowker's Tech	0.1177	0.7983***	0.675	1.63	2.58	2.95
LOC Tech	-0.0936	0.9274***	0.452	0.99	2.44	3.16
Computers	-0.1908	0.7539***	0.631	2.54	3.75	4.24
Comp+networks	-0.2911	0.7185***	0.463	2.97	5.06	5.80
Telecomm	-0.2492	0.2825***	0.317	7.03	8.16	8.37

Notes: ***,**,* denotes significance at the 1%, 5% and 10% levels respectively. The variance decomposition results are based on the following VAR: $Z_t = \alpha+\delta t+BZ_{t-1} +\varepsilon_t$ where, $Z_t = [\ln(Investment_t), \ln(Indicator_t)]'$.

Table 2. 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)	**0.0491**	1 (AB)	0.2300	2 (AB)	0.2117	1 (AB)
LOC New Tech Books (TECH2)	**0.0160** 0.4734	1 (B) 3 (A)	**0.0227**	2 (AB)	0.9286	1 (AB)
Computer Software & Hardware Books (COMP)	**0.09524** **0.02190**	1 (B) 2 (A)	**0.0912**	2 (AB)	0.2056	1 (AB)
Computer Software, Hardware & Network Books (COMP2)	**0.0968** **0.0124**	1 (B) 2 (A)	**0.0694**	2 (AB)	0.3088	1 (AB)
Telecommunications (TEL)	**0.0377**	1 (AB)	**0.0169**	2 (AB)	0.8889	1 (AB)
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)	0.5581	1 (AB)	**0.0945**	2 (AB)	0.4064	1 (AB)
LOC New Tech Books (TECH2)	0.2613 **0.0381**	1 (B) 3 (A)	0.3077	2 (AB)	**0.0227**	1 (AB)
Computer Software & Hardware Books (COMP)	0.2611 **0.0614**	1 (B) 2 (A)	**0.0149**	2 (AB)	0.9650	1 (AB)
Computer Software, Hardware & Network Books (COMP2)	0.1937 **0.0375**	1 (B) 2 (A)	**0.0137**	2 (AB)	0.9296	1 (AB)
Telecommunications (TEL)	0.5260	1 (AB)	0.7325	2 (AB)	0.8882	1 (AB)

Notes: (AB) indicates the lag length is selected by both the AIC and BIC, (A) indicates the lag length selected by the AIC, and (B) indicates the lag length selected by the BIC.

Table 3: Cross-Correlations Between Detrended GDP, Output per hour, TFP and Technology Indicators

		GDP_{t-2}	GDP_{t-1}	GDP_t	GDP_{t+1}	GDP_{t+2}	Y/L_{t-2}	Y/L_{t-1}	Y/L_t	Y/L_{t+1}	Y/L_{t+2}
	$TECH_t$	0.1395	0.0063	0.0482	0.3491	-0.2110	0.1168	0.1204	0.0510	-0.0538	-0.3271
	$TECH2_t$	0.0508	-0.2559	0.0123	0.1428	0.1307	-0.2325	-0.0213	0.2188	0.1241	0.0201
Business	$COMP_t$	-0.3463	-0.2017	0.2061	0.4748	0.0363	-0.2482	0.3207	0.3609	-0.0078	-0.1780
Cycle	$COMP2_t$	-0.3357	-0.1977	0.2066	0.4593	0.0278	-0.2487	0.3146	0.3502	-0.0178	-0.1639
Frequencies	TEL_t	0.0239	-0.0801	-0.4762	-0.0227	0.3319	-0.2501	-0.1453	-0.1940	0.3182	0.0767
	PAT_t	-0.0139	-0.0346	-0.1153	-0.1630	0.0145	-0.1602	-0.0893	-0.0627	-0.0902	0.2759
	$R\&D_t$	-0.2234	0.2185	0.3786	-0.0266	-0.2705	0.0621	0.3016	-0.1112	0.0149	0.0218
	$TECH_t$	-0.4099	-0.2534	-0.0402	0.2337	0.2371	-0.1199	0.0680	0.2270	0.3382	0.3360
	$TECH2_t$	-0.0222	-0.1302	0.0260	0.1532	0.2268	0.0709	0.1922	0.2927	0.2582	0.1800
Medium	$COMP_t$	-0.4720	-0.3559	-0.0698	0.2481	0.3572	-0.1122	0.2849	0.5110	0.5660	0.5500
Term Cycle	$COMP2_t$	-0.4976	-0.3791	-0.0823	0.2390	0.3492	-0.1353	0.2632	0.4871	0.5405	0.5337
Frequencies	TEL_t	-0.0425	0.0729	0.1044	0.4145	0.6003	0.2595	0.4141	0.4221	0.5533	0.3501
	PAT_t	0.4359	0.4009	0.3214	0.1929	0.1209	0.4291	0.3557	0.2333	0.0964	0.0619
	$R\&D_t$	-0.2216	-0.0176	0.1155	0.2131	0.3020	0.0429	0.2407	0.3802	0.5402	0.5735
		$TFP1_{t-2}$	$TFP1_{t-1}$	$TFP1_t$	$TFP1_{t+1}$	$TFP1_{t+2}$	$TFP2_{t-2}$	$TFP2_{t-1}$	$TFP2_t$	$TFP2_{t+1}$	$TFP2_{t+2}$
	$TECH_t$	0.1475	0.0700	0.0500	0.1453	-0.3451	0.0336	0.1199	0.0925	-0.0825	-0.2245
	$TECH2_t$	-0.1439	-0.1685	0.1673	0.1698	0.0735	-0.1502	0.0556	0.0330	0.1801	0.1778
Business	$COMP_t$	-0.3578	0.1207	0.3848	0.2527	-0.1354	-0.0182	0.1264	0.0174	0.0043	0.1734
Cycle	$COMP2_t$	-0.3527	0.1179	0.3776	0.2378	-0.1298	-0.0055	0.1227	-0.0023	0.0041	0.1877
Frequencies	TEL_t	-0.1793	-0.1401	-0.3641	0.2353	0.2505	-0.1642	-0.4197	0.0678	0.2757	-0.1941
	PAT_t	-0.1288	-0.0834	-0.0894	-0.1330	0.2049	-0.0092	-0.0300	-0.2488	-0.0738	0.4846
	$R\&D_t$	-0.0412	0.3499	0.1044	-0.0563	-0.1474	0.0605	0.0615	-0.0188	0.2445	-0.0881
	$TECH_t$	-0.2120	-0.0215	0.1713	0.3571	0.3215	-0.2685	-0.0490	0.1353	0.2439	0.3018
	$TECH2_t$	0.0495	0.0892	0.2591	0.3012	0.2675	0.1005	0.1336	0.0851	0.0961	0.0739
Medium	$COMP_t$	-0.2948	0.0462	0.3504	0.5344	0.5469	-0.1542	0.0692	0.2421	0.4211	0.5760
Term Cycle	$COMP2_t$	-0.3183	0.0264	0.3350	0.5178	0.5347	-0.1795	0.0399	0.2105	0.3968	0.5592
Frequencies	TEL_t	0.1430	0.3166	0.3379	0.5813	0.5173	0.2153	0.3003	0.5404	0.6160	0.3966
	PAT_t	0.4487	0.3896	0.2830	0.1384	0.1018	0.6105	0.5402	0.3578	0.2183	0.1484
	$R\&D_t$	-0.0477	0.1637	0.2934	0.4316	0.4905	-0.0592	0.1418	0.3480	0.5350	0.5865

Table 3 continued:

		INV_{t-2}	INV_{t-1}	INV_t	INV_{t+1}	INV_{t+2}	$Hours_{t-2}$	$Hours_{t-1}$	$Hours_t$	$Hours_{t+1}$	$Hours_{t+2}$
	$TECH_t$	0.2070	0.0736	0.0431	0.1850	-0.2251	0.0900	-0.0504	0.0261	0.3892	-0.0649
	$TECH2_t$	0.1142	-0.1384	0.0209	0.0970	0.0516	0.1630	-0.2566	-0.0908	0.0900	0.1266
Business	**$COMP_t$**	-0.3081	-0.1229	0.2227	0.4135	-0.0065	-0.2433	-0.3620	0.0438	0.4984	0.1221
Cycle	**$COMP2_t$**	-0.2967	-0.1194	0.2173	0.3986	-0.0132	-0.2320	-0.3550	0.0494	0.4869	0.1066
Frequencies	**TEL_t**	-0.0105	-0.2213	-0.4580	0.0135	0.4314	0.1433	-0.0146	-0.4043	-0.1744	0.3094
	PAT_t	-0.0550	-0.0520	-0.0711	-0.0873	0.0100	0.0614	0.0062	-0.0905	-0.1271	-0.1155
	$R\&D_t$	-0.1618	0.2467	0.4124	0.0082	-0.3058	-0.2622	0.0848	0.4472	-0.0348	-0.2921
	$TECH_t$	-0.0082	0.0680	0.1339	0.2202	0.0776	-0.3972	-0.3244	-0.1714	0.0768	0.0819
	$TECH2_t$	-0.1550	-0.2391	-0.0409	0.1491	0.2601	-0.0644	-0.2539	-0.1329	0.0301	0.1568
Medium	**$COMP_t$**	-0.3965	-0.3064	-0.0632	0.1973	0.2060	-0.4718	-0.5607	-0.3624	-0.0332	0.0991
Term Cycle	**$COMP2_t$**	-0.4063	-0.3021	-0.0421	0.2216	0.2253	-0.4880	-0.5749	-0.3632	-0.0294	0.0992
Frequencies	**TEL_t**	-0.1234	-0.0997	-0.0602	0.2548	0.4505	-0.1920	-0.1472	-0.1159	0.1622	0.4851
	PAT_t	0.0093	0.0244	0.0392	-0.0109	0.0039	0.2553	0.2564	0.2343	0.1648	0.1024
	$R\&D_t$	-0.0367	0.0205	-0.0204	-0.0659	-0.0874	-0.2745	-0.1534	-0.0802	-0.0584	0.0236

	σ_{GDP}	σ_{INVEST}	σ_{HOURS}	σ_{TFP1}	σ_{TFP2}	σ_{TECH}	σ_{TECH2}	σ_{COMP}	σ_{COMP2}	σ_{TEL}
Business Cycle Frequencies	0.0144	0.0472	0.0139	0.0071	0.0077	0.0759	0.0353	0.1868	0.1874	0.1264
Medium Term Cycle Frequencies	0.0267	0.0692	0.0236	0.0137	0.0187	0.1559	0.0506	0.3479	0.3375	0.1758

Table 4: P-values of Granger Causality Tests

Technology Indicator	Does Technology Granger-Cause GDP?	Does GDP Granger-Cause Technology?	Does Technology Granger-Cause Productivity Measures?			Does Productivity Grange-Cause Technology?		
			TFP 1	TFP2	Y/L	TFP 1	TFP 2	Y/L
Bowker's New Tech Books (TECH)	0.004	0.805	0.046	0.412	0.095	0.900	0.868	0.408
Library of Congress New Tech Books (TECH2)	0.015	0.872	0.153	0.808	0.195	0.486	0.052	0.113
Computer Software & Hardware Books (COMP)	0.002	0.282	0.007	0.018	0.068	0.504	0.928	0.607
Computer Software, Hardware & Networks (COMP2)	0.002	0.237	0.006	0.015	0.075	0.549	0.886	0.583
Telecommunications (TEL)	0.002	0.467	0.002	0.053	0.050	0.055	0.062	0.034
Patents (PAT)	0.480	0.418	0.816	0.800	0.619	0.670	0.896	0.433
Research & Development (RANDD) 2 lags	0.117	0.003	0.059	0.038	0.134	0.001	0.064	0.001
Bowker's new History Books (HIS)	0.528	0.275	0.600	0.285	0.661	0.132	0.163	0.109

Notes: For the cases of TECH, TECH2, COMP, COMP2, TEL, PAT, and HIS, $Y_t = \alpha+\gamma t+\rho Y_{t-1} +\varepsilon_t$, and for the case of R&D $Y_t = \alpha+\gamma t+\rho_1 Y_{t-1} +\rho_2 Y_{t-2} +\varepsilon_t$, where $Y_t = [\ln(GDP_t), \ln(X_t)]'$, $Y_t = [\ln(TFP_t), \ln(X_t)]'$ or $Y_t = [\ln(Y/L_t), \ln(X_t)]'$ and X_t is the value of the indicator at time t.

Table 5. Percent of Variation Due to Technology in Two Variable VARs

	Years	ln(GDP)	ln(TFP1)	ln(TFP2)	ln(Y/L)
Bowker's New Tech Books	3	15.02	7.19	1.13	5.54
(TECH)	6	37.59	20.30	3.92	14.84
	9	46.68	27.34	6.22	20.09
Library of Congress New Tech Books	3	9.43	3.08	0.07	3.05
(TECH2)	6	27.43	10.01	0.24	8.22
	9	37.67	15.02	0.39	11.30
Computer Software	3	18.41	16.44	13.30	7.55
& Hardware Books	6	42.25	35.87	30.76	17.15
(COMP)	9	49.55	41.95	38.03	21.50
Computer Software, Hardware	3	18.84	16.68	14.00	7.11
& Networks Books	6	40.99	34.21	30.63	15.46
(COMP2)	9	47.02	39.14	37.05	19.01
Telecommunications	3	22.61	19.41	5.85	7.96
(TEL)	6	30.73	24.05	7.10	10.42
	9	32.67	25.22	7.41	11.14
Patents	3	0.52	0.05	0.06	0.25
(PAT)	6	2.35	0.25	0.28	1.14
	9	4.61	0.52	0.56	2.34
R&D	3	0.43	0.25	3.87	0.69
2 lags	6	1.24	4.18	21.44	2.17
(RANDD)	9	3.90	10.55	33.10	6.66

Notes: These decompositions are based on bi-variate VARs where ln(GDP), ln(TFP) and ln(Y/L) are ordered first. For the cases of using the new book measures and patents the VAR takes the form $Y_t = \alpha+\gamma t+\rho Y_{t-1} + \varepsilon_t$, while for the case of R&D $Y_t = \alpha+\gamma t+\rho_1 Y_{t-1} + \rho_2 Y_{t-2} + \varepsilon_t$, where $Y_t = [\ln(GDP_t), \ln(X_t)]'$, $Y_t = [\ln(TFP_t), \ln(X_t)]'$ or $Y_t = [\ln(Y/L_t), \ln(X_t)]'$ and X_t is the value of the indicator at time t.

Table 6. Incremental change in goodness of fit.

Technology Indicator	GDP R-bar	GDP Change in R-Bar	TFP1 R-bar	TFP1 Change in R-Bar	TFP 2 R-bar	TFP 2 Change in R-Bar	Y/L R-bar	Y/L Change in R-Bar
None	0.9970		0.9917		0.8184		0.9960	
Bowker's New Tech Books (TECH)	0.9975	5.36E-04	0.9924	6.35E-04	0.8169	-1.50E-03	0.9962	1.89E-04
Library of Congress New Tech Books (TECH2)	0.9974	3.72E-04	0.9920	2.32E-04	0.8138	-4.61E-03	0.9961	7.40E-05
Computer Software & Hardware Books (COMP)	0.9976	5.97E-04	0.9930	1.28E-03	0.8399	2.14E-02	0.9963	2.43E-04
Computer Software, Hardware & Network Books (COMP2)	0.9976	6.19E-04	0.9931	1.32E-03	0.8412	2.28E-02	0.9962	2.26E-04
Telecommunications (TEL)	0.9976	6.20E-04	0.9934	1.63E-03	0.8316	1.32E-02	0.9963	2.94E-04
Patents (PAT)	0.9970	-3.80E-05	0.9915	-2.05E-04	0.8139	-4.58E-03	0.9959	-7.80E-05
R&D (RANDD)	0.9971	8.60E-05	0.9929	1.12E-03	0.8217	3.26E-03	0.9968	7.65E-04

Notes: These results are based on bi-variate VARs. For the cases of using the new book measures and patents the VAR takes the form $Y_t = \alpha+\gamma t+\rho Y_{t-1} +\varepsilon_t$, while for the case of R&D $Y_t = \alpha+\gamma t+\rho_1 Y_{t-1} +\rho_2 Y_{t-2} +\varepsilon_t$, where $Y_t = [\ln(GDP_t), \ln(X_t)]'$, $Y_t = [\ln(TFP_t), \ln(X_t)]'$ or $Y_t = [\ln(Y/L_t), \ln(X_t)]'$ and X_t is the value of the indicator at time t.

Table 7: P-values of Short-run - Causality Tests for Tr-variate VARs

Technology Indicator	Does Technology Granger-Cause GDP?	Does GDP Granger-Cause Technology?	Does Technology Granger-Cause Productivity Measures?			Does Productivity Grange-Cause Technology?		
			TFP 1	TFP2	Y/L	TFP 1	TFP 2	Y/L
Bowker's New Tech Books (TECH)	0.000	0.960	0.002	0.090	0.069	0.233	0.100	0.100
Library of Congress New Tech Books (TECH2)	0.004	0.891	0.016	0.297	0.164	0.456	0.017	0.092
Computer Software & Hardware Books (COMP)	0.002	0.245	0.004	0.013	0.072	0.704	0.652	0.559
Computer Software, Hardware & Networks (COMP2)	0.002	0.210	0.005	0.012	0.079	0.690	0.688	0.567
Telecommunications (TEL)	0.003	0.381	0.003	0.066	0.039	0.075	0.108	0.026
Patents (PAT)	0.007	0.033	0.107	0.374	0.507	0.002	0.034	0.001
Research & Development (RANDD) 2 lags	0.042	0.001	0.046	0.048	0.054	0.003	0.117	0.003
Bowker's new History Books (HIS)	0.489	0.253	0.588	0.250	0.671	0.169	0.254	0.117

Notes: For the cases of TECH, TECH2, COMP, COMP2, TEL, PAT, and HIS, $Y_t = \alpha+\gamma t+\rho Y_{t-1} +\varepsilon_t$, and for the case of R&D $Y_t = \alpha+\gamma t+\rho_1 Y_{t-1} +\rho_2 Y_{t-2} +\varepsilon_t$, where $Y_t = [\ln(BP_t), \ln(GDP_t), \ln(X_t)]'$, $Y_t = [\ln(BP_t), \ln(TFP_t), \ln(X_t)]'$ or $Y_t = [\ln(BP_t), \ln(Y/L_t), \ln(X_t)]'$ and X_t is the value of the indicator at time t.

Table 8: Percent of Variation Due to Technology Indicators and Stock Prices in the Tri-variate VARs

	Years	ln(GDP)		ln(TFP1)		Ln(TFP2)		ln(Y/L)	
		Indicator	BP	Indicator	BP	Indicator	BP	Indicator	BP
Bowker's New Tech Books	3	20.64	13.09	15.38	30.81	4.75	18.96	6.27	23.90
(TECH)	6	39.20	16.47	25.48	35.98	9.17	27.87	12.96	24.87
	9	42.65	16.06	27.12	37.21	10.34	32.13	15.37	23.57
Library of Congress	3	14.21	9.11	11.84	26.39	1.68	17.80	4.40	21.38
New Tech Books	6	34.20	12.16	22.84	31.14	2.58	27.06	10.11	21.27
(TECH2)	9	39.50	13.91	24.11	35.71	2.33	34.35	12.77	21.63
Computer Software	3	17.52	1.52	17.51	8.98	14.99	6.64	7.09	11.53
& Hardware Books	6	40.94	1.14	37.10	6.53	33.52	7.76	14.96	8.17
(COMP)	9	46.50	2.03	41.94	6.04	40.50	7.90	16.75	6.82
Computer Software, Hardware	3	17.82	1.19	17.36	8.34	15.52	6.34	6.85	11.48
& Networks Books	6	39.91	0.89	35.64	6.26	33.45	7.93	13.85	8.37
(COMP2)	9	44.79	1.37	40.04	5.82	39.80	8.75	15.37	7.03
Telecommunications	3	20.34	2.58	18.11	14.15	5.71	6.32	8.15	14.13
(TEL)	6	27.76	5.50	22.50	17.43	7.62	11.17	9.85	13.02
	9	29.33	8.90	23.45	20.72	8.36	16.63	10.18	12.07

Notes: For all cases $Y_t = \alpha+\gamma t+\rho Y_{t-1} +\varepsilon_t$, where $Y_t = [\ln(BP_t), \ln(GDP_t), \ln(X_t)]'$, $Y_t = [\ln(BP_t), \ln(TFP_t), \ln(X_t)]'$ or $Y_t = [\ln(BP_t), \ln(Y/L_t), \ln(X_t)]'$ and X_t is the value of the indicator at time t.

Table 9. Variation Due to Technology in the Four-Variable VAR

	Horizon	TFP1			TFP2		
	(In Years)	ln(Inv)	Δln(L)	ln(TFP)	Ln(Inv)	Δln(L)	ln(TFP)
Bowker's New Tech Books	3	3.36	5.03	8.65	5.48	6.48	1.82
(TECH)	6	10.35	6.41	15.40	13.06	7.48	4.56
	9	13.06	6.49	17.89	15.25	7.51	5.34
Library of Congress	3	2.07	0.02	1.16	3.46	0.24	0.34
New Tech Books	6	4.11	0.13	1.74	5.89	0.43	0.37
(TECH2)	9	4.74	0.19	2.01	6.16	0.58	0.36
Computer Software &	3	3.02	3.49	11.69	5.68	5.48	10.05
Hardware Books	6	10.02	4.65	21.03	16.60	6.91	21.45
(COMP)	9	12.60	4.68	23.62	19.83	6.92	24.23
Computer Software,	3	4.19	4.04	12.55	6.44	5.66	10.56
Hardware & Networks	6	11.51	4.79	20.27	17.13	6.75	21.07
(COMP2)	9	13.51	4.79	21.99	19.76	6.76	23.18
Telecommunications	3	7.51	1.68	18.83	3.75	0.36	10.81
(TEL)	6	10.71	1.57	17.61	5.60	0.40	10.39
	9	10.83	1.58	16.95	5.70	0.41	9.99

Notes: For all cases $Y_t = \alpha+\gamma t+\rho Y_{t-1} + \varepsilon_t$, where $Y_t = [\ln(Inv_t), \Delta\ln(L), \ln(TFP1_t), \ln(X_t)]'$, or $Y_t = [\ln(Inv_t), \Delta\ln(L), \ln(TFP2_t), \ln(X_t)]'$, and X_t is the value of the indicator at time t.

Appendix A. Sample Marc Record and Associated online display

Marc Record:

00971cam 2200277 a
45000010008000000050017000080080041000250350021000669060045000870100017001320200039001
49040001800188050002700206082001700233100002400250245005500274260004600329300002700375
440004600402504002500448500002000473650003600493740003800529952006000567991006600627-2
860358-20000328102341.0-850830s1986   mau   b   001 0 eng - 9(DLC)   85020087-
a7bcbccorignewd1eocipf19gy-gencatlg- a   85020087 - a020112078X (pbk.) :c$21.95
(est.)- aDLCcDLCdDLC-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.- 0aC++ (Computer program lan-
guage)-0 aC plus plus programming language.- aAnother issue (not in LC) has: viii,
328 p. ta01 4-3-87- bc-GenCollhQA76.73.C153iS77 1986p0003475293AtCopy 1wBOOKS-

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

Appendix B. 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

Appendix C: Detailed description of Variables and Data Sources

MARC21 Records: These records for the years 1968-1997 are obtainable from the Library of Congresses Cataloguing Distribution Service department. For the purposes of this investigation I focus on the set entitled Books in English. The records from 1955-1967 are from the REMARC database and were accessed through Thompson Dialogue.

Patents: The data on patent applications are available from the U.S. patent and trademark office at http://www.uspto.gov/web/offices/ac/ido/oeip/taf/h_counts.htm.

Industrial R&D expenditures: These statistics are available from the National Science foundation in Table E-1: The Trends in total (Federal plus company and other) U.S. industrial R&D performance (in current and constant $1996) at http://www.nsf.gov/statistics/srs01410/#top

GDP and components: These statistics are obtained from the Bureau of Economic Analysis' GDP and the National Income and Product Account (NIPA) Historical Table 1.2. Real Gross Domestic Product. [Billions of chained (1996) dollars]

Labour Hours: Data on Employee hours in the non-agricultural sectors (pneumonic LPMHU) are from Global Insight's Basic Economics database.

Population: The population data used in the total civilian non-institutional population obtainable from Global Insight's Basic Economics database (Series P16).

Capital Stock: The real capital stock series is the net stock of fixed reproducible tangible wealth in billions of chained (1996) dollars. This series is obtainable from Global Insight's Basic Economics database (Series KNIQ)

GDP Price Deflator: These data are from the Bureau of Economic Analysis' GDP and the National Income and Product Account (NIPA) Historical Table 7.1. Quantity and Price Indexes for Gross Domestic Product. [Index numbers, 1996=100].

Investment in equipment and software: The Quality index for investment in equipment and software is from the Bureau of Economic Analysis' GDP and the National Income and Product Account (NIPA) Historical Table 7.1. Quantity and Price Indexes for Gross Domestic Product. [Index numbers, 1996=100].

Wages, indirect taxes, subsidies and gross domestic income: These data are from the Bureau of Economic Analysis' GDP and the National Income and Product Account (NIPA) Historical Table 1.10. Gross Domestic Income by Type of Income. [Billions of dollars]

S&P Index: The annual series is the average value of the daily S&P'S Composite index computed using series FSPCOM from Global Insight's Basic Economics database**.**

Commodore 64 sales: The data is reported in Reimer (2005) and is available from Jermey Reimer's webpage http://www.pegasus3d.com/total_share.html.

Microsoft Windows 3.1 licenses: The number of Windows programs licensed were obtained from Gartner Dataquest's historical Press Releases.

TFP1: This series is calculated as: $TFP1_t = \Delta\ln(Y_t) - 0.5(\alpha_t + \alpha_{t-1})\Delta\ln(K_t) - (1-0.5(\alpha_t + \alpha_{t-1}))\Delta\ln L_t$ 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 hours worked. The elasticity of capital in time t and t-1, α_t and α_{t-1}, are computed using information on labor share based on data in the NIPA under the assumption that 70% of proprietors' income and taxes on production less subsidies are assigned to labor.

TFP2: This series is the corrected Solow residual created by Basu, Fernald and Kimball (2006).