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Read All about It!! What Happens Following a Technology Shock?

By Michelle Alexopoulos*

Existing indicators of technical change are plagued by shortcomings. I present 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* E22, E23, E32, O33, O34, O47)

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 (VARs)—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?

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[1] See e.g., Susanto Basu, John A. Fernald, and Miles S. Kimball (2006) for a discussion of factors contaminating Solow residuals, and potential reasons why long-run identifying restrictions may capture both technology and nontechnology shocks.

Most would agree that such an indicator should: (i) be available at least on an annual basis over a long time horizon, (ii) be objectively determined, (iii) be related to the date that a new product/process is brought to market, (iv) weight different technologies according to their importance or impact on the economy, and (v) 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 1955–1997, 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 United States). 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 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 on aggregate fluctuations while total factor productivity (TFP), 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 Galí (1999a), long-run restrictions in a VAR are used to identify the shocks.[4] In the second, Basu, Fernald, and Kimball (2006)—henceforth, BFK—attempt to correct the Solow residual by controlling for nontechnological 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. John Shea (1999), 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]

[2] See Jordi Galí and Pau 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 neoclassical 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 Paul Beaudry and Franck Portier (2006) and Nir Jaimovich and Sergio Rebelo (2006).

[4] This method is also seen in Galí and Rabanal (2004), Francis and Ramey (2005), Lawrence Christiano, Martin Eichenbaum, and Robert Vigfusson (2002, 2004; henceforth CEV), David Altig, Christiano, Eichenbaum, and Jesper Linde (2003)—henceforth, ACEL, and Jonas D. M. Fisher (2002).

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

While each of these has its strengths and its weaknesses,[6] my approach is closest to that of Shea (1999), 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 Galí's (1999a) approach, the results do not rely on the assumption that only technology shocks affect productivity in the long run, an assumption that would be 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 (1999)—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 (1999) 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 (1999) findings, in other words, are compromised by problems inherent in the use of R&D and patent 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 TFP and capital accumulation at both short- and medium-run horizons, have a strong, positive effect on GDP.[11]

The remainder of the paper is organized as follows. In Section I, 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 II, I present results, based on a series of VARs, that describe the relationship between the book-based indicators and GDP,

[6] See CEV (2004) and Galí and Rabanal (2004) for an exploration of the strengths and weaknesses of the first, Shea (1999) and Christiano, Eichenbaum, and Vigfusson (2004) for the second, and Galí (1999b) and Adam B. Jaffe (1999b) for the third.

[7] See, e.g., Eliezer Geisler (2000). As he notes, fewer than 20 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 the 1998 Macroeconomics Annual, pp. 320–21).

[9] See Alexopoulos and Jon Cohen (2011) for some evidence about the lags between the discovery of a product and its commercialization.

[10] Fisher (2002) 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 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., Daniel Wilson 2004).

productivity, and inputs. Similar to the findings of Fisher (2002), CEV (2002, 2004) and ACEL (2003), my findings 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, TFP, and investment all increase after one year, with the peak impact occurring three to four 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 III, I conclude and offer suggestions for future research.

I. Measurement

A. *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 Zvi 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.

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 United States 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 US 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: (i) measures of knowledge production inputs,

[12] These findings are in partial contrast to those presented in Galí (1999a), Neville Francis and Valerie A. 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 (2002) have argued that: (i) Galí's (1999a) and Francis and Ramey's (2005) results are driven by their assumption that hours worked is not a stationary series, and (ii) if one assumes hours worked is stationary, their methodology predicts that positive technology shocks are expansionary. Moreover, CEV (2004) argue that measurement error may explain the results found by BFK (2006).

[13] Fisher (2002) finds, unlike others, that investment-specific shocks have a very large impact on labor.

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

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

like research and development expenditures, and (ii) 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 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.

B. *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 United States 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 book titles by major subject fields used by American libraries to keep track of new publications available in the United States. Each year from 1955 to 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 United States. Later they are based on information obtained from the Library of Congress 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

[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 release manuals when they introduce new technologies.

[18] The CIP 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.

widely than those of smaller houses, and, second, to capture the major technological advances.

Bowker's estimates, referred to as the TECH series below, do suffer from three potential drawbacks, however. 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).

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 United States, 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 to 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 United States. The Library of Congress Classification Code is what librarians use to group books on similar topics (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

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

[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 subgroupings in T and Q. The Library of Congress Classification differs from the Dewey Decimal System used to compile the Bowker 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.

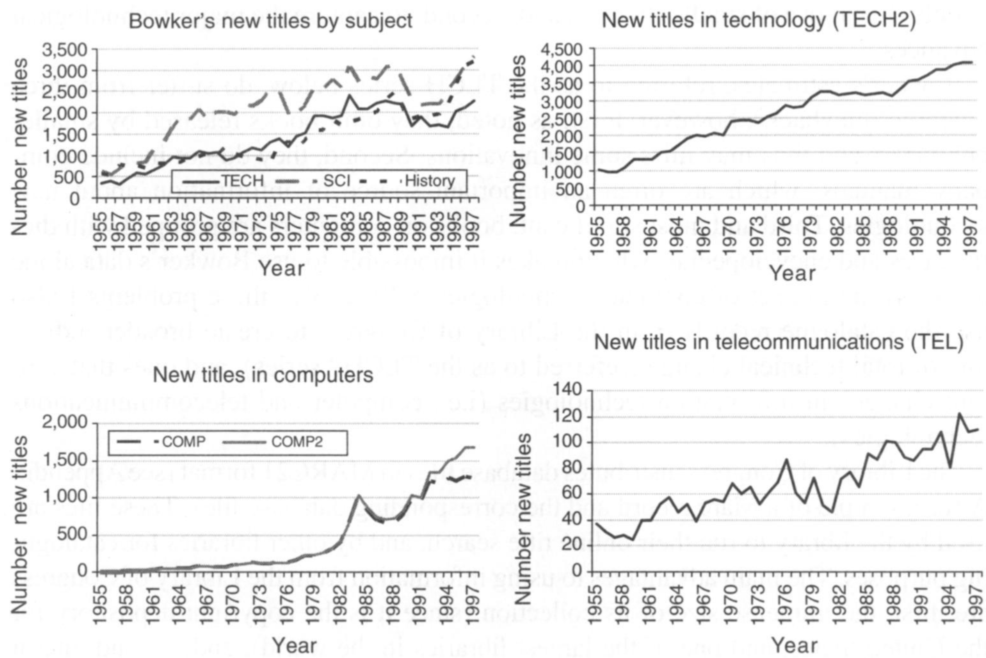

FIGURE 1. THE INDICATORS

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.

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 latter to show that new history titles, as a proxy for other nontechnical types of publications in general, do not share the same relationship with productivity and GDP that the technology series do.

C. *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

[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.

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 1980–1984 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 Analysis (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 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 illustrate, 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 coincide with the date of the commercialization and clearly precedes the vast majority of sales (the measure of diffusion).

The second panel in Figure 2B reveals a similar pattern for a very popular software product—Microsoft Windows 3.1. Introduced in April 1992, it 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

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

[25] A similar pattern 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.

[26] See Alexopoulos and Cohen (2011, 2009) for more case studies that demonstrate that the measures are more related to introduction of new technologies than to the diffusion of the new technologies over the last century.

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

Panel A.

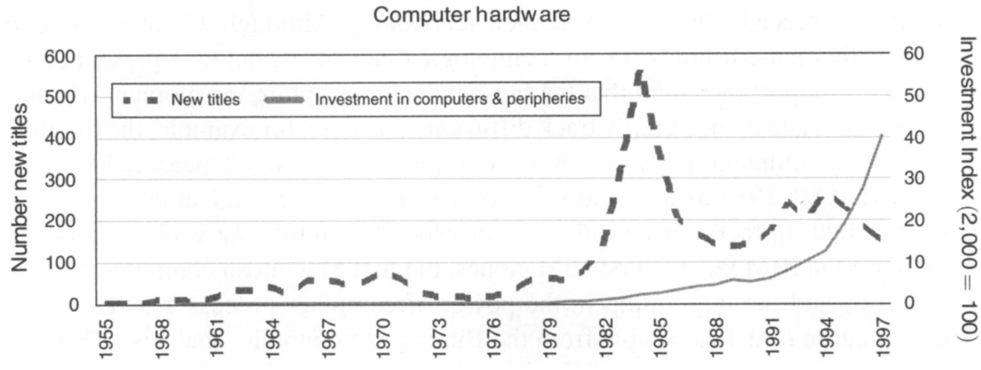

FIGURE 2A. NEW HARDWARE TITLES, INVESTMENT AND TIMELINE

Notes: 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 first 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 and IBM 7030 marketed
1962	Magnetic storage tape introduced and 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 and 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
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	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

Panel B.

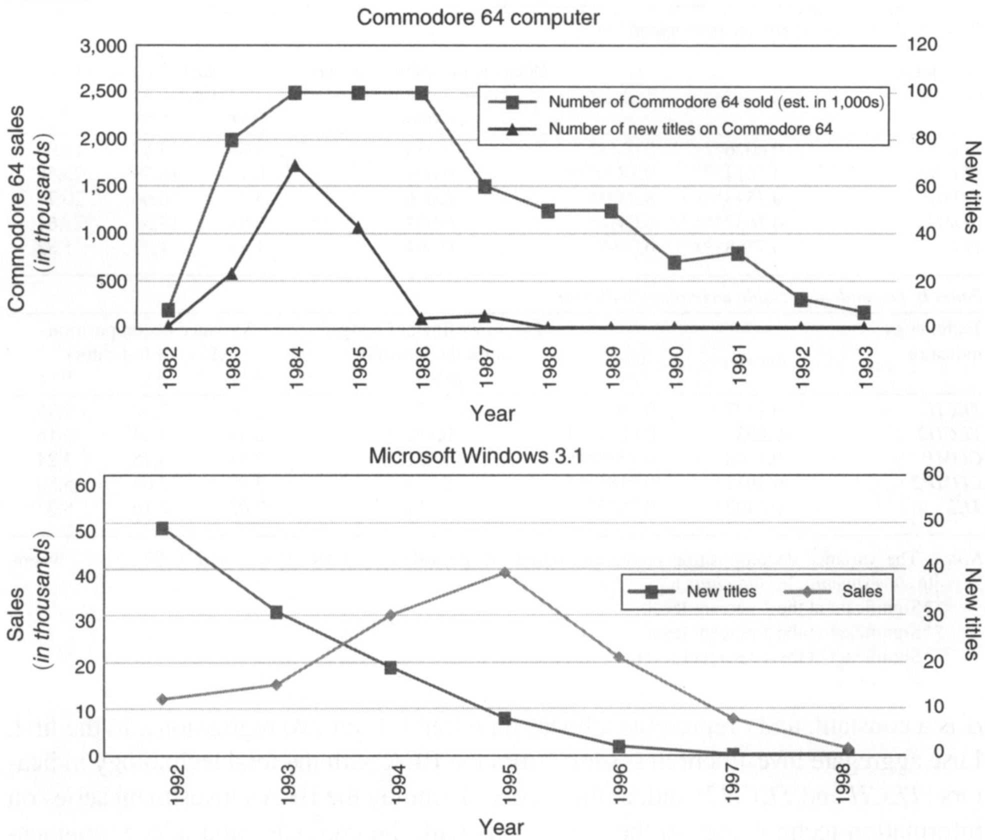

FIGURE 2B

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). For Microsoft Windows 3.1, the number of new titles is based on the Library of Congress' MARC21 files and the sales data is obtainable from Gartner Dataquest.

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.

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 bivariate system:

$$Z_t = \alpha + \delta t + BZ_{t-1} + \varepsilon_t, \text{ where, } Z_t = [\ln(\mathit{Investment}_t), \ln(\mathit{Indicator}_t)]',^{29}$$

$$B = \begin{bmatrix} \beta_{investment} & \beta_{indicator} \\ \gamma_{investment} & \gamma_{indicator} \end{bmatrix},$$

[28] The number of Windows programs licensed was obtained from Gartner Dataquest's historical press releases.

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

TABLE 1—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
TECH	0.6026***	0.0756**	0.036	4.88	12.57	15.98
TECH2	0.5614***	0.1829***	0.002	6.14	18.79	25.58
COMP	0.7573***	0.0424*	0.086	5.79	16.06	20.79
COMP2	0.7632***	0.0474*	0.057	6.84	17.51	21.61
TEL	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 Indicator) 3 yr	6 yr	9 yr
TECH	0.1177	0.7983***	0.675	1.63	2.58	2.95
TECH2	−0.0936	0.9274***	0.452	0.99	2.44	3.16
COMP	−0.1908	0.7539***	0.631	2.54	3.75	4.24
COMP2	−0.2911	0.7185***	0.463	2.97	5.06	5.80
TEL	−0.2492	0.2825***	0.317	7.03	8.16	8.37

Notes: The variance decomposition results are based on the following VAR: $Z_t = \alpha + \delta_t + BZ_{t-1} + \varepsilon_t$, where, $Z_t = [\ln(Investment_t), \ln(Indicator_t)]'$.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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 positive—relationship between the new titles and investment. This latter 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]

D. *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.

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

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 technology books (*TECH*)	0.0491	1 (AB)	0.2300	2 (AB)	0.2117	1 (AB)
Library of Congress technology books (*TECH2*)	0.0160 0.4734	1 (B) 3 (A)	0.0227	2 (AB)	0.9286	1 (AB)
Computer software and hardware books (*COMP*)	0.09524 0.02190	1 (B) 2 (A)	0.0912	2 (AB)	0.2056	1 (AB)
Computer software, hardware, and network books (*COMP2*)	0.0968 0.0124	1 (B) 2 (A)	0.0694	2 (AB)	0.3088	1 (AB)
Telecommunications books (*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 technology books (*TECH*)	0.5581	1 (AB)	0.0945	2 (AB)	0.4064	1 (AB)
Library of Congress technology books (*TECH2*)	0.2613 0.0381	1 (B) 3 (A)	0.3077	2 (AB)	0.0227	1 (AB)
Computer software and hardware books (*COMP*)	0.2611 0.0614	1 (B) 2 (A)	0.0149	2 (AB)	0.9650	1 (AB)
Computer software, hardware, and network books (*COMP2*)	0.1937 0.0375	1 (B) 2 (A)	0.0137	2 (AB)	0.9296	1 (AB)
Telecommunications books (*TEL*)	0.5260	1 (AB)	0.7325	2 (AB)	0.8882	1 (AB)

Note: (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.

The question, then, is: do patents, science books,[31] or R&D expenditures Granger-cause the number of new titles in technology?[32] Based on the numbers reported in Table 2, it appears that the answer is yes.[33] The results are displayed for the number of lags selected by both the BIC and the 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 are 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 feedback between technology and science since new technology titles often Granger-cause both

[31] The Bowker measure of new science titles includes books published by major publishers in the United States.

[32] The data on the number of patent applications by year can be obtained from the US 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 Saul Lach 1995) is used instead of the flow.

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 bivariate systems indicate that innovations in industrial R&D, while important, account for less than 30 percent of the variation of the new technology measures.[35]

II. Analyzing the Impact of Technical Change

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 Basic Economics database (formally known as Citibase) and the BEA national accounts database.[36] In addition, I use two measures for total factor productivity (TFP)—*TFP1* is 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 nonconstant returns to scale.[37]

A. *Relationship between GDP, Productivity, and the New Measures of Technology*

Figure 3 depicts changes in the technological indicator obtained from the Bowker 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, Tables 3A to 3D report a selection of standard deviations and cross correlations of the data detrended with the band-pass filter suggested by Christiano and Terry J.

[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.

[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 nonagriculture, nonmining business economy and ends in 1996.

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

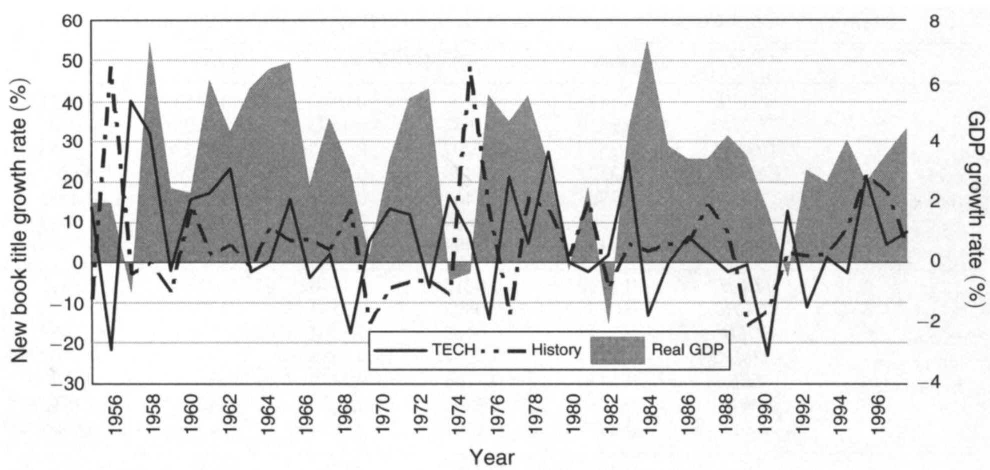

FIGURE 3. RELATIONSHIP BEWTEEN GDP AND NEW TITLES

TABLE 3A—CROSS CORRELATIONS BETWEEN DETRENDED GDP, INVESTMENT, AND TECHNOLOGY INDICATORS

		GDP_{t-2}	GDP_{t-1}	GDP_t	GDP_{t+1}	GDP_{t+2}
Business cycle frequencies	$TECH_t$	0.1395	0.0063	0.0482	0.3491	−0.2110
	$TECH2_t$	0.0508	−0.2559	0.0123	0.1428	0.1307
	$COMP_t$	−0.3463	−0.2017	0.2061	0.4748	0.0363
	$COMP2_t$	−0.3357	−0.1977	0.2066	0.4593	0.0278
	TEL_t	0.0239	−0.0801	−0.4762	−0.0227	0.3319
	PAT_t	−0.0139	−0.0346	−0.1153	−0.1630	0.0145
	$R\&D_t$	−0.2234	0.2185	0.3786	−0.0266	−0.2705
Medium-term cycle frequencies	$TECH_t$	−0.4099	−0.2534	−0.0402	0.2337	0.2371
	$TECH2_t$	−0.0222	−0.1302	0.0260	0.1532	0.2268
	$COMP_t$	−0.4720	−0.3559	−0.0698	0.2481	0.3572
	$COMP2_t$	−0.4976	−0.3791	−0.0823	0.2390	0.3492
	TEL_t	−0.0425	0.0729	0.1044	0.4145	0.6003
	PAT_t	0.4359	0.4009	0.3214	0.1929	0.1209
	$R\&D_t$	−0.2216	−0.0176	0.1155	0.2131	0.3020
		INV_{t-2}	INV_{t-1}	INV_t	INV_{t+1}	INV_{t+2}
Business cycle frequencies	$TECH_t$	0.2070	0.0736	0.0431	0.1850	−0.2251
	$TECH2_t$	0.1142	−0.1384	0.0209	0.0970	0.0516
	$COMP_t$	−0.3081	−0.1229	0.2227	0.4135	−0.0065
	$COMP2_t$	−0.2967	−0.1194	0.2173	0.3986	−0.0132
	TEL_t	−0.0105	−0.2213	−0.4580	0.0135	0.4314
	PAT_t	−0.0550	−0.0520	−0.0711	−0.0873	0.0100
	$R\&D_t$	−0.1618	0.2467	0.4124	0.0082	−0.3058
Medium-term cycle frequencies	$TECH_t$	−0.0082	0.0680	0.1339	0.2202	0.0776
	$TECH2_t$	−0.1550	−0.2391	−0.0409	0.1491	0.2601
	$COMP_t$	−0.3965	−0.3064	−0.0632	0.1973	0.2060
	$COMP2_t$	−0.4063	−0.3021	−0.0421	0.2216	0.2253
	TEL_t	−0.1234	−0.0997	−0.0602	0.2548	0.4505
	PAT_t	0.0093	0.0244	0.0392	−0.0109	0.0039
	$R\&D_t$	−0.0367	0.0205	−0.0204	−0.0659	−0.0874

Fitzgerald (2003). Since technology may affect both the short-run business cycle and the medium-run cycle discussed by Diego Comin and Mark 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),

TABLE 3B—CROSS CORRELATIONS BETWEEN DETRENDED TFP AND TECHNOLOGY INDICATORS

		$TFP1_{t-2}$	$TFP1_{t-1}$	$TFP1_t$	$TFP1_{t+1}$	$TFP1_{t+2}$
Business cycle frequencies	$TECH_t$	0.1475	0.0700	0.0500	0.1453	−0.3451
	$TECH2_t$	−0.1439	−0.1685	0.1673	0.1698	0.0735
	$COMP_t$	−0.3578	0.1207	0.3848	0.2527	−0.1354
	$COMP2_t$	−0.3527	0.1179	0.3776	0.2378	−0.1298
	TEL_t	−0.1793	−0.1401	−0.3641	0.2353	0.2505
	PAT_t	−0.1288	−0.0834	−0.0894	−0.1330	0.2049
	$R\&D_t$	−0.0412	0.3499	0.1044	−0.0563	−0.1474
Medium-term cycle frequencies	$TECH_t$	−0.2120	−0.0215	0.1713	0.3571	0.3215
	$TECH2_t$	0.0495	0.0892	0.2591	0.3012	0.2675
	$COMP_t$	−0.2948	0.0462	0.3504	0.5344	0.5469
	$COMP2_t$	−0.3183	0.0264	0.3350	0.5178	0.5347
	TEL_t	0.1430	0.3166	0.3379	0.5813	0.5173
	PAT_t	0.4487	0.3896	0.2830	0.1384	0.1018
	$R\&D_t$	−0.0477	0.1637	0.2934	0.4316	0.4905
		$TFP2_{t-2}$	$TFP2_{t-1}$	$TFP2_t$	$TFP2_{t+1}$	$TFP2_{t+2}$
Business cycle frequencies	$TECH_t$	0.0336	0.1199	0.0925	−0.0825	−0.2245
	$TECH2_t$	−0.1502	0.0556	0.0330	0.1801	0.1778
	$COMP_t$	−0.0182	0.1264	0.0174	0.0043	0.1734
	$COMP2_t$	−0.0055	0.1227	−0.0023	0.0041	0.1877
	TEL_t	−0.1642	−0.4197	0.0678	0.2757	−0.1941
	PAT_t	−0.0092	−0.0300	−0.2488	−0.0738	0.4846
	$R\&D_t$	0.0605	0.0615	−0.0188	0.2445	−0.0881
Medium-term cycle frequencies	$TECH_t$	−0.2685	−0.0490	0.1353	0.2439	0.3018
	$TECH2_t$	0.1005	0.1336	0.0851	0.0961	0.0739
	$COMP_t$	−0.1542	0.0692	0.2421	0.4211	0.5760
	$COMP2_t$	−0.1795	0.0399	0.2105	0.3968	0.5592
	TEL_t	0.2153	0.3003	0.5404	0.6160	0.3966
	PAT_t	0.6105	0.5402	0.3578	0.2183	0.1484
	$R\&D_t$	−0.0592	0.1418	0.3480	0.5350	0.5865

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 nontrivial 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 Patrick Francois and Huw Lloyd-Ellis (2006).

B. *Bivariate Systems*

To explore the extent of the relationship between the new measures, output, and productivity, I estimate a series of bivariate 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 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

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

Table 3C—Cross Correlations between Detrended Hours, Output per Hour, and Technology Indicators

		$Hours_{t-2}$	$Hours_{t-1}$	$Hours_t$	$Hours_{t+1}$	$Hours_{t+2}$
Business cycle frequencies	$TECH_t$	0.0900	−0.0504	0.0261	0.3892	−0.0649
	$TECH2_t$	0.1630	−0.2566	−0.0908	0.0900	0.1266
	$COMP_t$	−0.2433	−0.3620	0.0438	0.4984	0.1221
	$COMP2_t$	−0.2320	−0.3550	0.0494	0.4869	0.1066
	TEL_t	0.1433	−0.0146	−0.4043	−0.1744	0.3094
	PAT_t	0.0614	0.0062	−0.0905	−0.1271	−0.1155
	$R\&D_t$	−0.2622	0.0848	0.4472	−0.0348	−0.2921
Medium-term cycle frequencies	$TECH_t$	−0.3972	−0.3244	−0.1714	0.0768	0.0819
	$TECH2_t$	−0.0644	−0.2539	−0.1329	0.0301	0.1568
	$COMP_t$	−0.4718	−0.5607	−0.3624	−0.0332	0.0991
	$COMP2_t$	−0.4880	−0.5749	−0.3632	−0.0294	0.0992
	TEL_t	−0.1920	−0.1472	−0.1159	0.1622	0.4851
	PAT_t	0.2553	0.2564	0.2343	0.1648	0.1024
	$R\&D_t$	−0.2745	−0.1534	−0.0802	−0.0584	0.0236
		Y/L_{t-2}	Y/L_{t-1}	Y/L_t	Y/L_{t+1}	Y/L_{t+2}
Business cycle frequencies	$TECH_t$	0.1168	0.1204	0.0510	−0.0538	−0.3271
	$TECH2_t$	−0.2325	−0.0213	0.2188	0.1241	0.0201
	$COMP_t$	−0.2482	0.3207	0.3609	−0.0078	−0.1780
	$COMP2_t$	−0.2487	0.3146	0.3502	−0.0178	−0.1639
	TEL_t	−0.2501	−0.1453	−0.1940	0.3182	0.0767
	PAT_t	−0.1602	−0.0893	−0.0627	−0.0902	0.2759
	$R\&D_t$	0.0621	0.3016	−0.1112	0.0149	0.0218
Medium-term cycle frequencies	$TECH_t$	−0.1199	0.0680	0.2270	0.3382	0.3360
	$TECH2_t$	0.0709	0.1922	0.2927	0.2582	0.1800
	$COMP_t$	−0.1122	0.2849	0.5110	0.5660	0.5500
	$COMP2_t$	−0.1353	0.2632	0.4871	0.5405	0.5337
	TEL_t	0.2595	0.4141	0.4221	0.5533	0.3501
	PAT_t	0.4291	0.3557	0.2333	0.0964	0.0619
	$R\&D_t$	0.0429	0.2407	0.3802	0.5402	0.5735

Table 3D—Selected Standard Deviations

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

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 affects only the variables of interest with a lag.[40] Based on the results of the BIC, a lag length of one was selected for each

[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.

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?		
			TFP1	*TFP2*	*Y/L*	*TFP1*	*TFP2*	*Y/L*
Bowker's technology books (*TECH*)	0.004	0.805	0.046	0.412	0.095	0.900	0.868	0.408
Library of Congress new technology books *TECH2*)	0.015	0.872	0.153	0.808	0.195	0.486	0.052	0.113
Computer software and hardware books (*COMP*)	0.002	0.282	0.007	0.018	0.068	0.504	0.928	0.607
Computer software, hardware, and network books (*COMP2*)	0.002	0.237	0.006	0.015	0.075	0.549	0.886	0.583
Telecommunications books (*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 and development (*RANDD*)	0.117	0.003	0.059	0.038	0.134	0.001	0.064	0.001
Bowker's 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 $Y_t = [\ln(\mathrm{GDP}_t), \ln(X_t)]'$, $Y_t = [\ln(TFP_t), \ln(X_t)]'$ or $Y_t = [\ln(Y/L_t), \ln(X_t)]'$ and X_t is the value of the indicator at time t.

of the systems, with the exception of the R&D, where a lag length of two was chosen.[41] Overall, the results of these VARs will: (i) document the relationship between the new publication-based indicators and the variables of interest, (ii) determine how the results using the new measures differ from those using the traditional patent and R&D measures, and (iii) 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 bivariate 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 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 three-, six-, and nine-year horizons. Three results

[41] For most cases, the BIC and AIC selected the same lag length. Since the results are virtually identical, I 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: (i) are unlikely to be correlated with changes in technology that could have an impact on economic activity, and (ii) would be affected by changes in the publishing industry.

TABLE 5—PERCENT OF VARIATION DUE TO TECHNOLOGY IN TWO VARIABLE VARS

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

Notes: These decompositions are based on bivariate 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.

are worth highlighting. First, the percent of variation in ln(*GDP*) due to technology at a three-year horizon is approximately 10–20 percent, with this effect doubling over the next three 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 account for only 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 to 4 years.[44]

[43] The results reported in Table 5 are similar to those from trivariate 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.

Table 6—Incremental Change in Goodness of Fit

	GDP		*TFP1*		*TFP2*		*Y/L*	
Technology indicator	$\overline{R}^2$	Change in $\overline{R}^2$	$\overline{R}^2$	Change in $\overline{R}^2$	$\overline{R}^2$	Change in $\overline{R}^2$	$\overline{R}^2$	Change in $\overline{R}^2$
None	0.9970		0.9917		0.8184		0.9960	
Bowker's technology 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 technology books (*TECH2*)	0.9974	3.72E-04	0.9920	2.32E-04	0.8138	−4.61E-03	0.9961	7.40E-05
Computer software and 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, and network books (*COMP2*)	0.9976	6.19E-04	0.9931	1.32E-03	0.8412	2.28E-02	0.9962	2.26E-04
Telecommunications books (*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 bivariate 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.

Moreover, at the peak, a one-standard-deviation shock results in a 0.008 to 0.014 percent 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 bivariate 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 to the productivity measures than the *TECH2* series, which may be an indication that 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

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

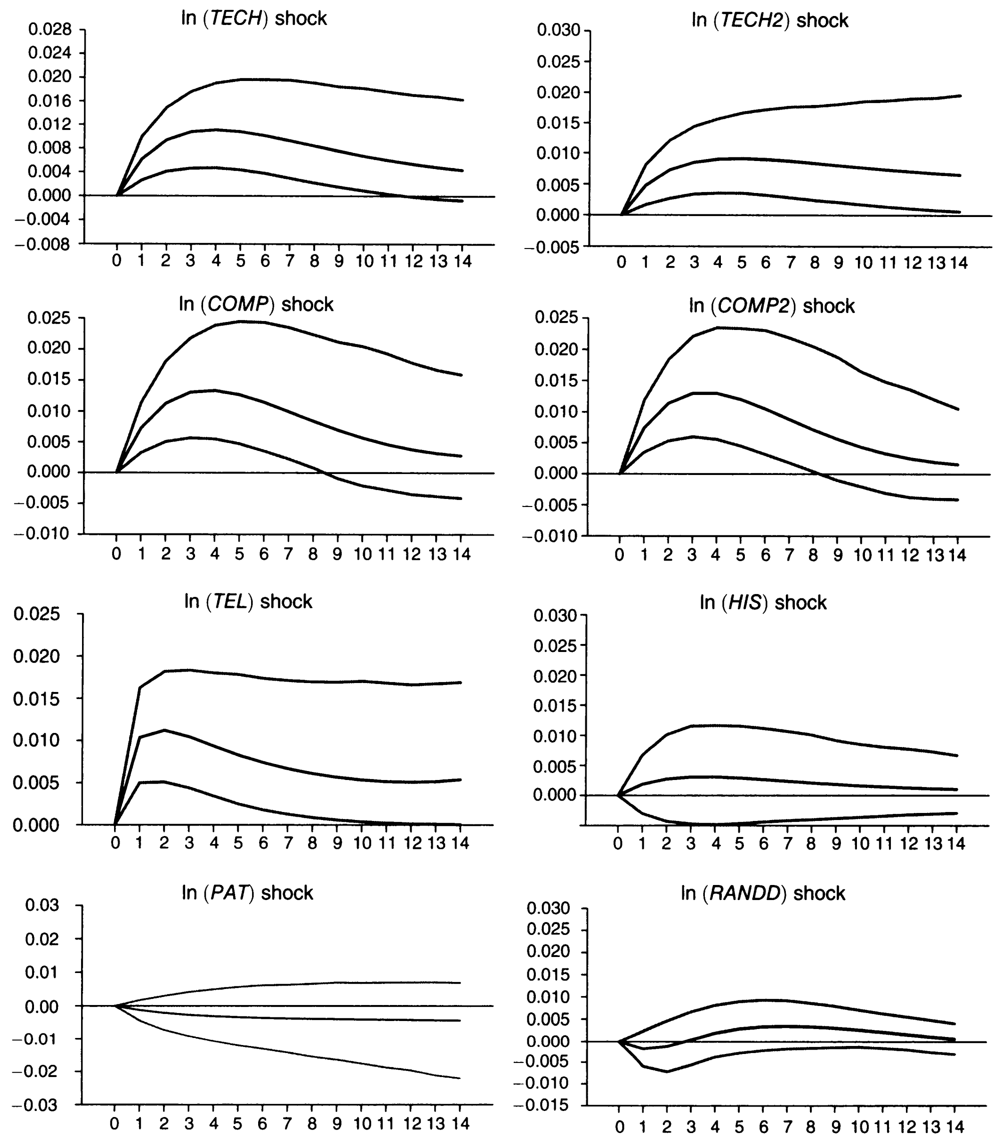

Figure 4. Response of Output to Technology Shocks and a History Shock

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 bivariate GDP VARs, and Table 6 reports the incremental change in

[46] These results echo the ones Shea found using use and manufacturing patents from 1959 to 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.

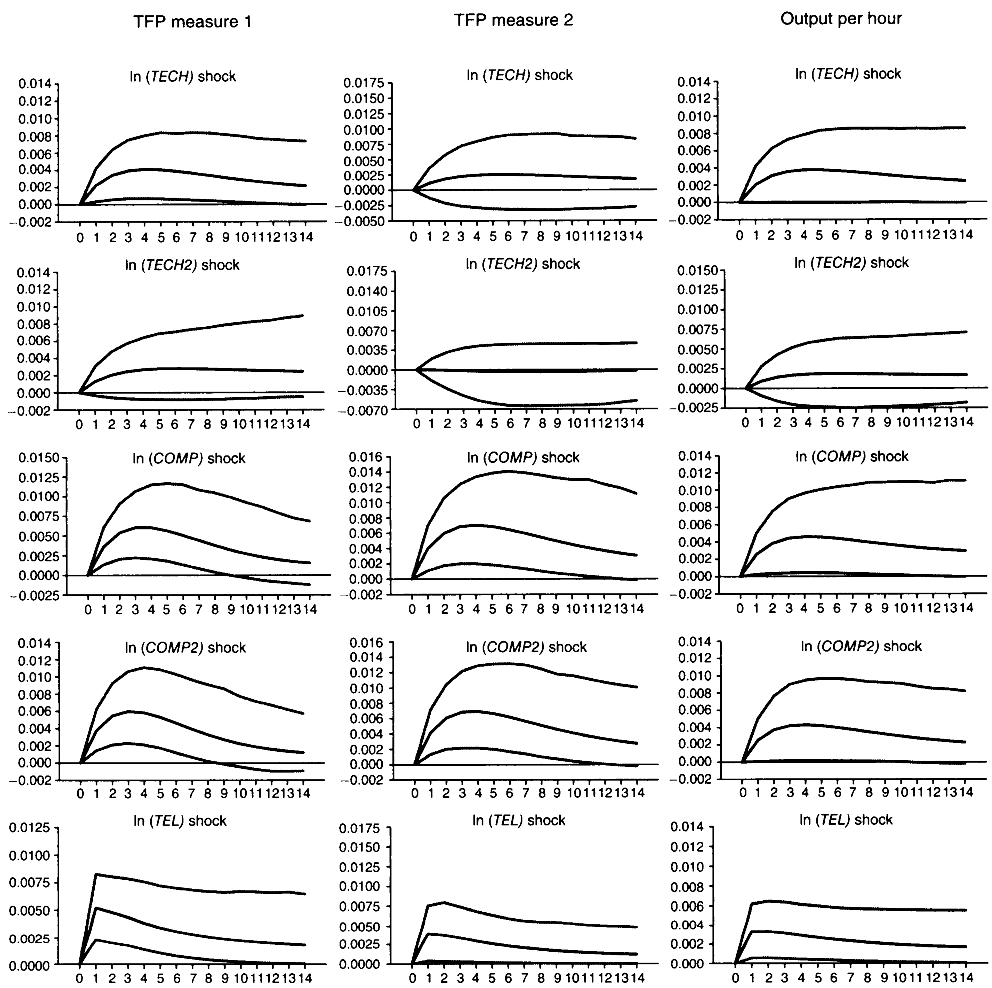

Figure 5. Responses of Productivity Measures to Technology Shocks

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 nontrivial 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 to 0.006 percent, 0.004 to 0.007 percent, and 0.003 to 0.004 percent, respectively.[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.

C. *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, 8A, and 8B 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 Standard & Poor's 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, it 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 Tables 8A and 8B demonstrate, the percent of variation in GDP and the productivity measures that can be attributed to the new technology 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

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

[48] The table also indicates that patents Granger-cause *GDP* at a 1 percent level and almost Granger-cause *TFP1* at a 10 percent 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 (1999) study.

TABLE 7—p-VALUES OF SHORT-RUN CAUSALITY TESTS FOR TRIVARIATE VARs

Technology indicator	Does technology Granger-cause GDP?	Does GDP Granger-cause technology?	Does technology Granger-cause productivity measures? *TFP1*	*TFP2*	*Y/L*	Does productivity Grange-cause technology? *TFP1*	*TFP2*	*Y/L*
Bowker's technology books (*TECH*)	0.000	0.960	0.002	0.090	0.069	0.233	0.100	0.100
Library of Congress technology books (*TECH2*)	0.004	0.891	0.016	0.297	0.164	0.456	0.017	0.092
Computer software and hardware books (*COMP*)	0.002	0.245	0.004	0.013	0.072	0.704	0.652	0.559
Computer software, hardware, and network books (*COMP2*)	0.002	0.210	0.005	0.012	0.079	0.690	0.688	0.567
Telecommunications books (*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 and development (*RANDD*)	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 $Y_t = [\ln(\text{BP}_t), \ln(\text{GDP}_t), \ln(X_t)]'$, $Y_t = [\ln(\text{BP}_t), \ln(\text{TFP}_t), \ln(X_t)]'$ or $Y_t = [\ln(\text{BP}_t), \ln(Y/L_t), \ln(X_t)]'$, and X_t is the value of the indicator at time t.

TABLE 8A—PERCENT OF VARIATION DUE TO TECHNOLOGY INDICATORS AND STOCK PRICES IN THE TRIVARIATE VARs

	Years	ln(*GDP*) *Indicator*	ln(*GDP*) *BP*	ln(*Y/L*) *Indicator*	ln(*Y/L*) *BP*
Bowker's technology books (*TECH*)	3	20.64	13.09	6.27	23.90
	6	39.20	16.47	12.96	24.87
	9	42.65	16.06	15.37	23.57
Library of Congress technology books (*TECH2*)	3	14.21	9.11	4.40	21.38
	6	34.20	12.16	10.11	21.27
	9	39.50	13.91	12.77	21.63
Computer software and hardware books (*COMP*)	3	17.52	1.52	7.09	11.53
	6	40.94	1.14	14.96	8.17
	9	46.50	2.03	16.75	6.82
Computer software, hardware, and network books (*COMP2*)	3	17.82	1.19	6.85	11.48
	6	39.91	0.89	13.85	8.37
	9	44.79	1.37	15.37	7.03
Telecommunications (*TEL*)	3	20.34	2.58	8.15	14.13
	6	27.76	5.50	9.85	13.02
	9	29.33	8.90	10.18	12.07

Notes: For all cases, $Y_t = \alpha + \gamma t + \rho Y_{t-1} + \varepsilon_t$, where $Y_t = [\ln(BP_t), \ln(GDP_t), \ln(X_t)]'$, 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.

productivity measures all increase in response to the technology shocks identified by my new indicators.

TABLE 8B—PERCENT OF VARIATION DUE TO TECHNOLOGY INDICATORS AND STOCK PRICES IN THE TRIVARIATE VARS

		ln(*TFP1*)		Ln(*TFP2*)	
	Years	*Indicator*	*BP*	*Indicator*	*BP*
Bowker's technology books (*TECH*)	3	15.38	30.81	4.75	18.96
	6	25.48	35.98	9.17	27.87
	9	27.12	37.21	10.34	32.13
Library of Congress technology books (*TECH2*)	3	11.84	26.39	1.68	17.80
	6	22.84	31.14	2.58	27.06
	9	24.11	35.71	2.33	34.35
Computer software and hardware books (*COMP*)	3	17.51	8.98	14.99	6.64
	6	37.10	6.53	33.52	7.76
	9	41.94	6.04	40.50	7.90
Computer software, hardware, and network books (*COMP2*)	3	17.36	8.34	15.52	6.34
	6	35.64	6.26	33.45	7.93
	9	40.04	5.82	39.80	8.75
Telecommunications books (*TEL*)	3	18.11	14.15	5.71	6.32
	6	22.50	17.43	7.62	11.17
	9	23.45	20.72	8.36	16.63

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

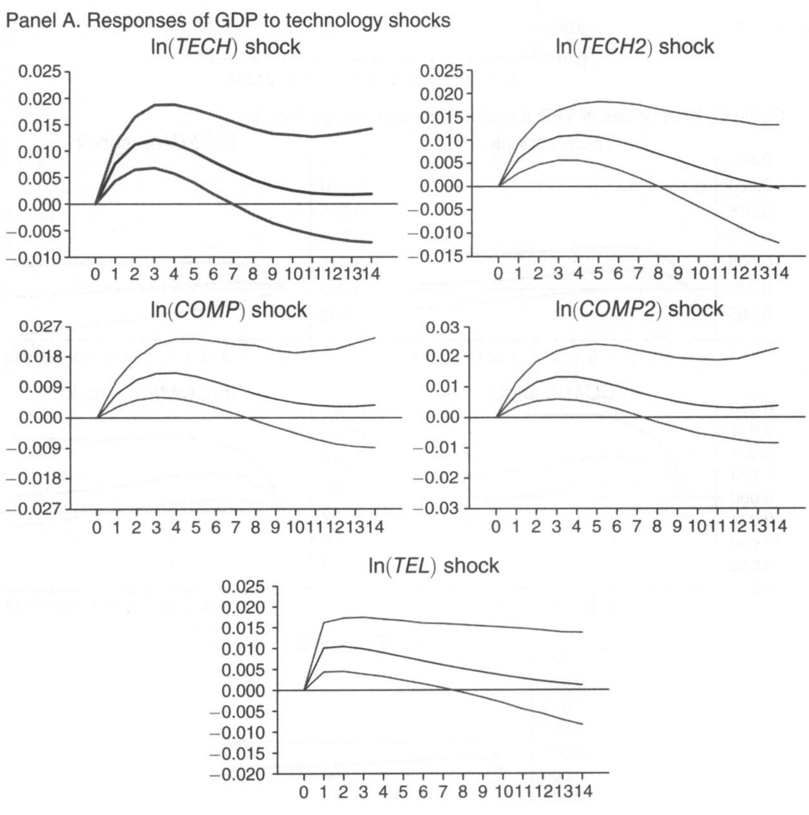

FIGURE 6 (*Continued*)

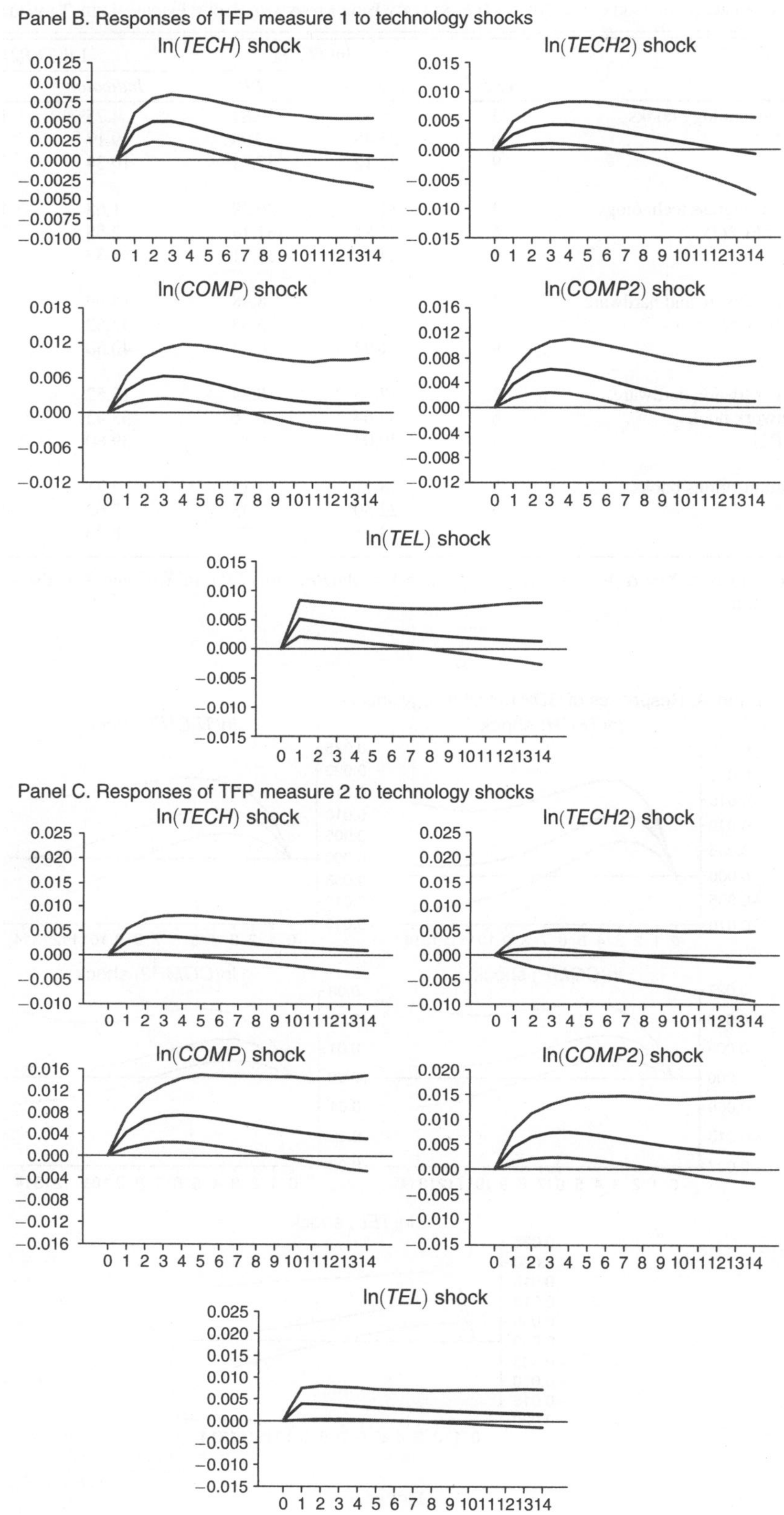

FIGURE 6 (Continued)

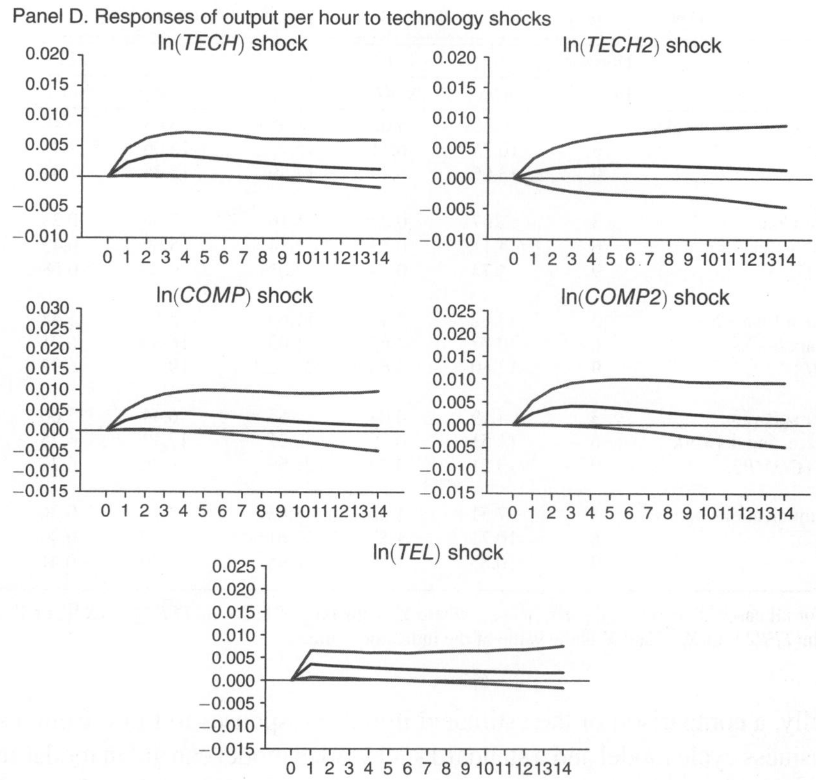

FIGURE 6 (*Concluded*)

D. *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 neoclassical 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 affect only 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 *COMP* and *COMP2*), once again, explaining the highest percent of variation in productivity.[49]

[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.

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 technology 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
technology 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 and	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, and network	6	11.51	4.79	20.27	17.13	6.75	21.07
books (*COMP2*)	9	13.51	4.79	21.99	19.76	6.76	23.18
Telecommunications books	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 $Y_t = [\ln(Inv_t), \Delta\ln(L_t), \ln(TFP1_t), \ln(X_t)]'$, or $Y_t = [\ln(Inv_t), \Delta\ln(L_t), \ln(TFP2_t), \ln(X_t)]'$, and X_t is the value of the indicator at time t.

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 Galí (1999a) 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 to four periods after the shock. The increase in TFP is generally significant for approximately four to five years following a shock to computer or telecommunications technologies. In contrast, 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.

III. Concluding Remarks

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, coincide with the date

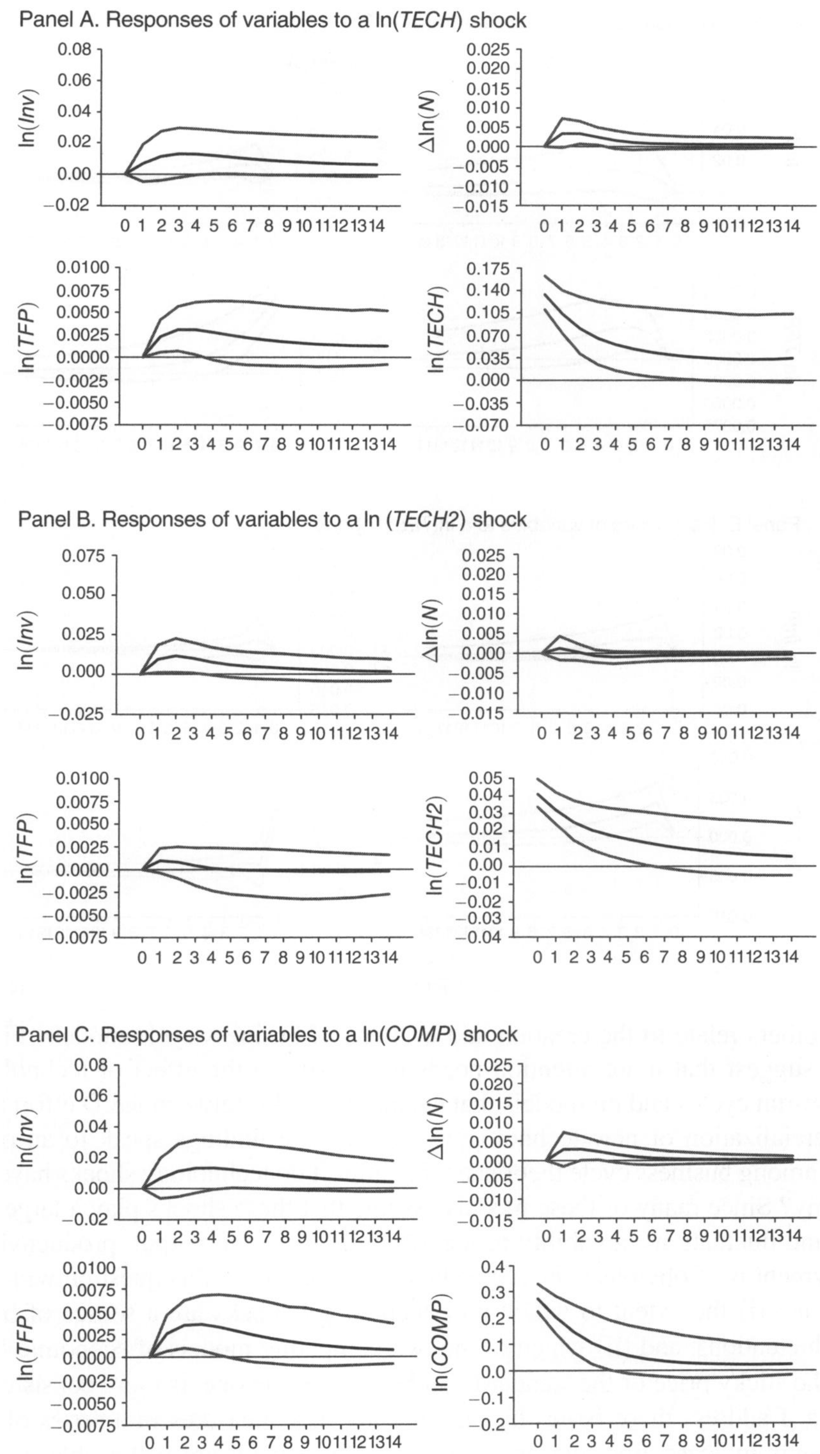

FIGURE 7 (*Continued*)

that new products/processes hit the market, and are positively related to inputs into knowledge production (such as scientific advances and R&D).

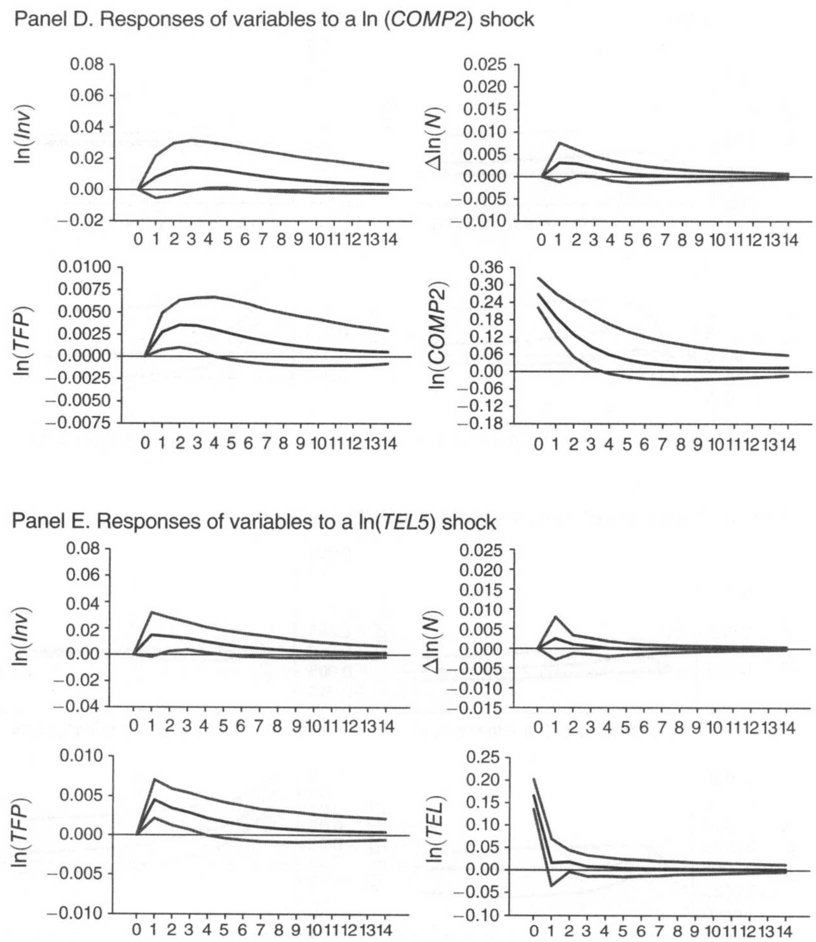

FIGURE 7 (*Concluded*)

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: (i) the extent to which pure technology shocks are a source of business cycle fluctuations, and (ii) 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 VARs. 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 variables. 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.

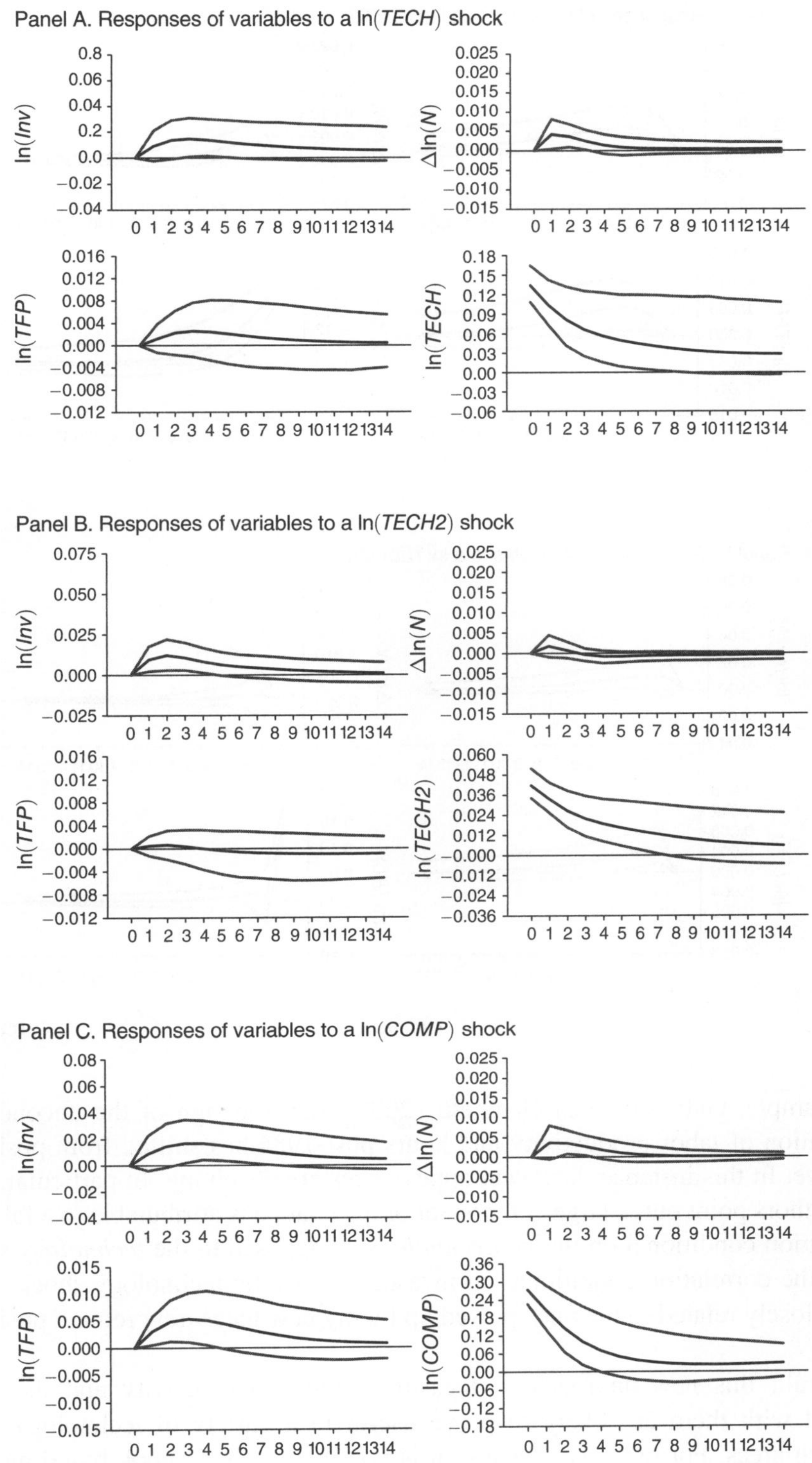

FIGURE 8 (*Continued*)

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,

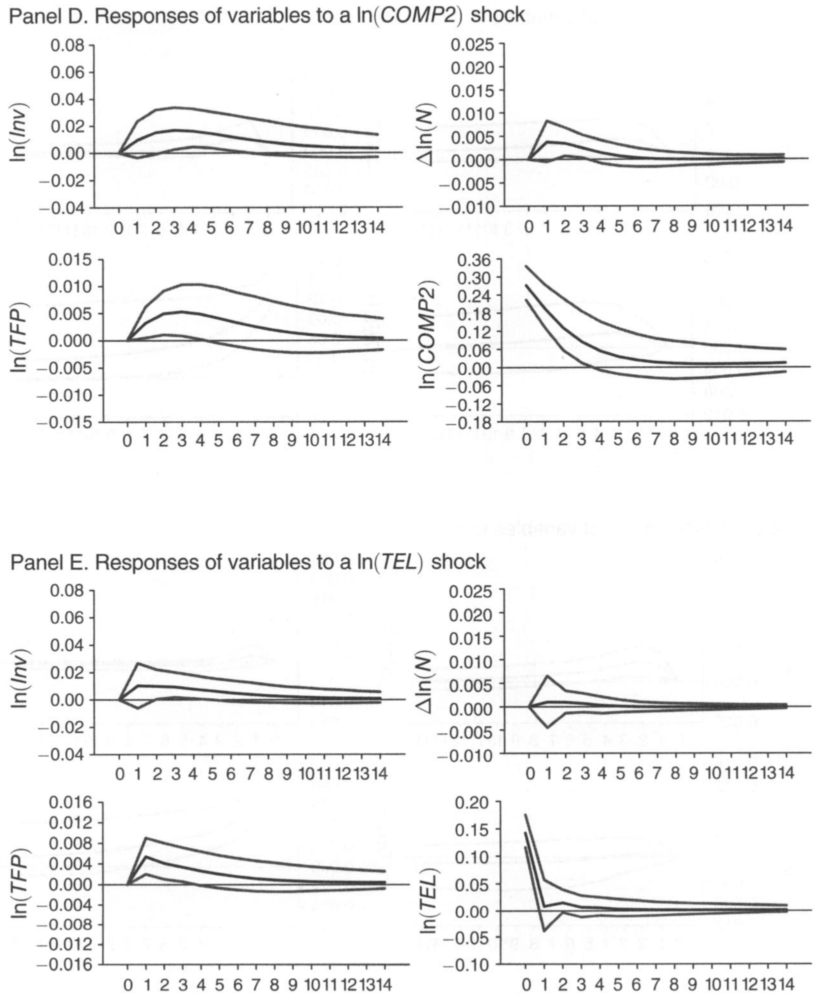

FIGURE 8 (*Concluded*)

for example, Galí and Luca Gambetti (2008), that the sign of the unconditional correlation of labor productivity and hours post-1984 has shifted from positive to negative. In this instance, however, appearances 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 *nontechnology* as opposed to the *technology* shocks, while the correlation conditional on investment-specific technology shocks (those most closely related to the ones picked up by my new measures) 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., David Ross and Klaus 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.

Appendix A: Sample Marc Record and Associated Online Display

Marc Record


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0200047365000360049374000380052995200600056799100660062
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aStroustrup, Bjarne.-14aThe C++ programming lan-
guage /cBjarne Stroustrup.- aReading, Mass.
:bAddison-Wesley,cc1986.- aviii, 327 p. ;c24
cm.- 0aAddison-Wesley series in computer sci-
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(Computer program language)-0 aC plus plus program-
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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.
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Subjects:	C++ (Computer program language)
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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 Congress Cataloguing Distribution Service Department. For the purposes of this investigation, I focus on the set entitled Books in English. The records from 1955 to 1967 are from the REMARC database and were accessed through Thompson Dialogue.

Patents: The data on patent applications are available from the US 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) US industrial R&D performance (in current and constant 1996 dollars): 1953–1999 in Research and Development in Industry, 1999 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 nonagricultural sectors (pneumonic LPMHU) are from Global Insight's Basic Economics database.

Population: The population data used in the total civilian noninstitutional 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 Composite Index computed using series FSPCOM from Global Insight's Basic Economics database.

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

Microsoft Windows 3.1 Licenses: The number of Windows programs licensed per year was 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}, is computed using information on labor share based on data in the NIPA under the assumption that 70 percent 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).

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