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The Impact of Technological Change

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Abstract

In this paper, I introduce novel measures of technological change, based on counts of books in the field of technology and technological standardization, in an otherwise standard vector autoregressive model, to show the relative importance of unanticipated productivity shocks, technology shocks, and anticipated productivity (news) shocks, in driving macroeconomic fluctuations. The results indicate that news shocks play a more important role than technology shocks at business cycle frequencies, while in the medium- to long-run technology shocks take the lead. Unanticipated productivity shocks do not seem to be a significant source of aggregate fluctuations regardless of the forecast horizon.

Keywords

productivity shock, technology shock, news shock, business cycle, structural vector autoregressive model

JEL Classification

C32, E32, O33

1 Introduction

The aim of this paper is to contribute to the ongoing debate on the role played by different productivity shocks in driving macroeconomic fluctuations and in particular to shed some light on the impact of technological change on economic activity.

The macroeconomic literature is far from reaching a consensus on which are the shocks that affect productivity and how important these shocks are for the rest of the economy. Following the reasoning proposed by the real business cycle (RBC) literature, aggregate productivity is affected immediately and permanently only by technology shocks and these shocks are the main driving force of cyclical fluctuations.[1] However, studies that take a more microeconomic perspective of technological progress observe that there is a considerable time lag between the invention of new technologies and their adoption in production at such a large scale as the diffusion to be reflected in measures of aggregate productivity.[2] Hence, the shock defined in the RBC literature to be the only shock with immediate effect on productivity cannot be a technology shock. For this reason, I prefer to further call it an unanticipated productivity shock. Moreover, empirical studies also question the RBC idea that this shock is the main source of macroeconomic fluctuations.[3]

With the unanticipated productivity shock being neither a technology shock, nor an important driver of aggregate fluctuations, other approaches have been taken to identify technology shocks and to measure the impact of technological change on economic activity. One is to apply identification schemes to identify technology shocks from macroeconomic data. For example, Beaudry and Portier (2004) and Beaudry and Portier (2006) state that, while technologies need time to diffuse and increase aggregate productivity, economic agents receive news about them early on. This information about future potential productivity gains encourages them to respond immediately in order to be among the first to benefit from the adoption of the new technologies. The coordination of agents' actions may lead to an increase in consumption and investment, and consequently in output, in anticipation of the change in productivity determined by technological innovations. On these premises, Beaudry and Portier (2006) impose short-run restrictions in a vector autoregressive model to identify an anticipated productivity (news) shock. They define the news shock to be the shock with no immediate effect on productivity, which has immediate effect on a forward looking variable. The idea is that forward looking variables, such as stock prices, or measures of consumer (business) confidence, capture the news about emerging technologies that potentially increase future productivity. They find that the news shock has no short-run effect on productivity, but afterwards it leads

[1]For details, see Kydland and Prescott (1982).

[2]Eden and Nguyen (2016) show that in the US the adoption lag is about twenty years for the technologies invented in the last two centuries and that in the recent years technologies have been adopted faster than in the past.

[3]See Basu et al. (2006) and Galí (1999), among others, for details on the estimation approach and results using total factor productivity in the first and labor productivity in the latter.

to a permanent increase in total factor productivity (TFP). In this respect, the news shock seems to match the slow diffusion of new technologies in productivity as indicated by micro studies. Moreover, Beaudry and Portier (2006) show that news shocks drive business cycle fluctuations. Barsky and Sims (2011) and Beaudry et al. (2011) propose the use of medium-run restrictions as an alternative method to identify news shocks. The definition of Beaudry et al. (2011) is that the news shock is the shock orthogonal to contemporaneous TFP movements that contributes the most to TFP's forecast error variance (FEV) at a finite medium-run horizon. This definition of the news shock is even closer to what is expected from a technology shock, i.e. to have no significant short-run effect on TFP given the slow diffusion of the technology, but to be a major source of fluctuations in productivity in the medium- and long-run. The findings of Beaudry et al. (2011) are similar to those of Beaudry and Portier (2006).[4]

The results reported in the empirical news literature have the drawback of being highly dependent on the identification schemes employed. Consequently, another approach proposed is the use of direct measures of technological change in the empirical analysis. Some earlier proposals of indicators were the number of patents, or data on R&D expenditures. However, as shown in Baron and Schmidt (2017), these are proxies for inventive activities, which may or may not translate into new technologies. The reason is that at the time of invention it is hard to predict the future use, profitability, or commercialization date of products using the new technology. In the recent years, two new proxies were proposed. The first was made by Alexopoulos (2011), who uses new book titles in the category technology as proxy for the adoption of technological innovations. She finds that technology shocks identified using the book-based indicators are an important source of economic fluctuations. Moreover, she shows that TFP, investment, and labor increase following a technology shock. The second proposal belongs to Baron and Schmidt (2017) and is an indicator based on the counts of standards in the categories information and communication technologies (ICT) and electronics. Baron and Schmidt (2017) claim that standardization precedes the implementation of new technologies and signals future productivity gains. This makes the technology shock identified using the standards-based indicator conceptually very similar to an anticipated productivity (news) shock, as defined in the empirical news literature. Baron and Schmidt (2017) find that TFP, output, and investment have an S-shaped response to a technology shock, which indicates that new technologies diffuse slowly, but have significant medium- and long-run effects on macroeconomic variables. They also show that forward looking variables respond immediately to technology shocks, which is in line with the predictions of the news literature.

In this paper, I take an empirical approach to investigate which of these three shocks plays a more important role in driving macroeconomic fluctuations: the unanticipated

[4]For an analysis of this literature see Bolboaca and Fischer (2017b), Beaudry and Portier (2014), and Ramey (2016), among others.

productivity shock, the technology shock, or the anticipated productivity (news) shock. The unanticipated productivity shock is the only shock with immediate effect on aggregate productivity. The technology shock is the shock on the measure of technological change that has no instantaneous effect on TFP. The news shock is the shock on the index of consumer sentiment, which affects TFP and the technological change indicator with a lag.

My findings indicate that the two technological change indicators I employ, i.e. based on either book titles or standardization, give similar results. Following a technology shock, TFP does not respond for several years, but then it gradually increases until it stabilizes at a new long-run level. This goes against the idea that technology shocks should affect immediately productivity, but matches the slow diffusion of technologies in the economy, as indicated by studies of micro data. Macroeconomic aggregates are also unaffected by the technology shock on impact, but start responding positively to the shock soon afterwards and increase for several quarters until they stabilize at higher new permanent levels. When comparing the technology shock with the other shocks, I observe that the technology shock has much stronger short- and medium-run effects on all macroeconomic variables than the unanticipated productivity shock. The unanticipated productivity shock has positive immediate effects on almost all macroeconomic variables, with the exception of consumption on which the effect is almost nil and hours worked for which the response is significantly negative, thus confirming the conclusion of Galí (1999) and Basu et al. (2006) that the unanticipated productivity shock is not expansionary.

An important comparison which, to the best of my knowledge, has not been done previously in the literature is between the technology and the news shock identified with short-run restrictions, when both shocks are identified in the same model. I find that the differences between the two shows are mostly apparent in the short-run. The instantaneous effect of the news shock on investment, output, and hours worked is significantly higher than the one of the technology shock. With the exception of hours worked and the index of consumer sentiment, all variables stabilize at higher permanent levels following a news shock. However, these long-run levels are slightly lower than those reached after a technology shock hits the economy.

I also find that these three shocks have different roles in driving macroeconomic fluctuations, depending on the forecast horizon. The unanticipated productivity shock explains most of the fluctuations of TFP in the short-run, but does not seem to play an important role in driving macroeconomic fluctuations either in the short-run, or in the medium-run, as its contribution to the variation in macroeconomic variables is small at all forecast horizons. This once again contradicts the RBC literature that assigns a central role to the unanticipated productivity shock in driving economic fluctuations. When comparing the relative importance of the other two shocks, it is evident that the news shock plays a more important role than the technology shock at business cycle frequencies, while in the medium- to long-run the technology shock takes the lead.

Furthermore, I draw a parallel between a news shock identified with the medium-run identification scheme, the news shock obtained using short-run restrictions, and the technology shock. My findings indicate that the news shock obtained using medium-run restrictions is virtually a mixture of the technology shock and the news shock obtained with short-run restrictions.[5] However, depending on the truncation horizon, this shock may resemble more either the news shock obtained with short-run restrictions, or the technology shock.

This paper contributes to the empirical literature on productivity shocks[6] with the introduction of the technological change indicator in an otherwise standard linear vector autoregressive setting and the identification of technology shocks along with the unanticipated and anticipated productivity shocks. Moreover, it contributes to the recent literature that develops direct measures of technological change (e.g. Alexopoulos (2011), Alexopoulos and Cohen (2011), and Baron and Schmidt (2017)) by making a comparison of several indicators and evaluating their performance in a horse-race of potential important sources of macroeconomic fluctuations. Finally, with the results obtained in this paper, I aim to contribute to the theoretical literature that investigates the effect of technology shocks on economic activity. In particular, this paper provides empirical evidence in favor of theoretical models that depart from the exogeneity assumption on productivity and which allow for a slow diffusion of technology into aggregate productivity.[7]

The rest of the paper is organized as follows. In the next section I describe the direct measures of technological change employed. In section 3, I present the empirical approach, and the different identification schemes. Section 4 then gives an overview of the results and section 5 concludes.

2 Measures of Technological Change

2.1 Book-Based Indicators

Following Alexopoulos (2011), the first measure of technological change I use is the book-based indicator obtained with data from the R.R. Bowker company, henceforth Bowker.[8] According to Peters (1992), Bowker provides statistics regarding the US publishing industry since 1880, but started reporting the number of new book titles and editions based

[5]The news shock identified with the medium-run identification scheme is obtained along with the unanticipated productivity shock, but not with the other two shocks.

[6] Ramey (2016) offers a recent survey of the empirical literature on macroeconomic shocks, including the different types of productivity shocks.

[7]See, for example, Comin et al. (2009), and Bolboaca and Fischer (2017a), among others.

[8]Bowker is the world's leading provider of bibliographic information, which offers tools and resources, such as the Books In Print database and Identifier Services. Bowker is also the official ISBN (International Standard Book Number) Agency for the US. More information is available on the company's website: `http://www.bowker.com/`.

on subject category only from 1950 onward (Nord and Miller (2009)). Alexopoulos (2011) employs the annual series for the categories technology, science, and history, for the sample period 1955-1997. My intuition for the reason why she did not consider more recent data is that until 1998 Bowker used the American Book Publishing Record database, which counted only the books categorized by the Library of Congress, while from then on they switched to the Books in Print database. This change of the procedure created a level shift in the series. In 2006, Bowker made another change of the methodology, but they restated the numbers for 2002-2005 data using the new approach in order to provide comparable prior year data.[9]

Using various sources,[10] I construct the annual series for the categories technology and science, for the sample period 1955-2012. As previously discussed, the time series have two breaks, one in 1998 and the other in 2002.[11] In order to use this data for empirical analysis, one approach is to employ sub-samples of the unadjusted time series. Given the annual frequency of the data, the only subsample long enough to be considered is the one ranging from 1955 to 1997, as it is done in Alexopoulos (2011). For the comparability of my results with those obtained in the aforementioned paper, I call the indicator based on the new titles published on the subject technology, TECH97, and the one on the subject science, SCI97.[12] However, reducing the sample to the period prior to 1998 makes the indicators miss some important technological advances that occurred in the decade from 2000 to 2010. For example, on what concerns the technology indicator, there were major developments in ICT such as WI-FI, Internet search engines, GPS, smart phones, USB flash drives, and Bluetooth, among others, which are discarded by reducing the sample to the period prior to the 2000s. Another important information that is neglected is the tech bubble burst in 2000, the years of technology recession that followed, and the rebound from 2003 on. Hence, in order to use the data for the whole sample period, i.e. 1955-2012, I construct break-adjusted level data by fixing the level for the reference period to the latest available data point,[13] and recursively dividing by one-period growth rates to generate values for all other periods before the reference period.[14] The annual series

[9]Details on the changes implied by the latest methodology are presented in the ISBN Annual Output Reports available online on Bowker's website (`http://www.bowker.com/tools-resources/Bowker-Data.html`).

[10]Details concerning the data sources are presented in Appendix A.

[11]The second break occurred in 2006, but given that the data has been adjusted for the period 2002-2005, the break is currently apparent in 2002.

[12] In Alexopoulos (2011) the indicators are named TECH and SCI, respectively. Throughout this paper I add to these names the last two digits of the year corresponding to the last data point in the sample.

[13]The choice of the reference point is arbitrary, but in practice either the first or the latest available data point is chosen as reference period. In this particular case the choice of the latest available data point seems more reasonable since Bowker motivated the switch to the new methodology in 1998 by stating that the old approach undercounted the number of publications.

[14]For obtaining the values corresponding to the year 2001 and 1997, the growth rate used for the division is the average of the antecedent and subsequent one-period growth rates.

for the categories technology, and science, both with level-breaks and break-adjusted, are displayed in Figure 10, and Figure 11, in Appendix B.

The book-based indicators obtained with data from Bowker have several drawbacks, some of them being signaled already by Alexopoulos (2011). One criticism is that the classification of titles in one of the twenty-three categories is done based on the Dewey Decimal Classification. According to Peters (1992), the Dewey Decimal numbers for each category are: Technology (600-609; 620-629; 660-669) and Science (500-599). This implies that category technology, for example, contains also dictionaries and encyclopedias (603), or books on the history of technologies (609). Alexopoulos (2011) points also to the fact that, while these categories include some books which do not actually belong there, they also disregard some valuable materials such as company's product manuals, or books released by small publishers. To this list I would also add the non-traditional books.[15] By computing the ratio between the traditional and non-traditional annual title output as reported by Bowker (2017), in 2002 there were six times more traditional books printed, while in 2012 the figures indicate the opposite. The difference is arguably even bigger given that Bowker's figures are based on the number of ISBNs registered, and thus it does not include the non-traditional books without ISBNs (Bradley et al. (2011)). Besides the non-traditional prints, audiobooks and e-books are also excluded, which may downward bias the counts mainly for the more recent years. Given these limitations of Bowker's series, it seems reasonable to use also other proxies for technological change.

Alexopoulos (2011) proposes a second set of book-based indicators, which are constructed using catalog records from the Library of Congress, henceforth LC. LC claims to be the largest library in the world, with more than 164 million items at the level of 2016, and to have one of the world's most extensive and diverse collection of scientific and technical information.[16] In the US, LC is also involved in various cataloging and recording activities of bibliographical data, and in particular it provides libraries with MARC (machine-readable cataloging) records that contain information about bibliographic items. Alexopoulos and Cohen (2011) argue that the dataset of MARC records is *virtually a complete list of all major new titles copyrighted within the US across a vast range of topics.* Both Alexopoulos (2011) and Alexopoulos and Cohen (2011), use a technological change indicator based on the MARC records in the subgroup T, which corresponds to the field of technology, and another two more specific indicators for the categories telecommunications and computer software and hardware, respectively. In this paper, I only consider the indicator of total technological change, referred to as the TECH2 series in Alexopoulos (2011), mainly for testing the robustness of the Bowker's

[15]According to Bowker's reports (e.g. Bowker (2017)), category non-traditional *consists of reprints (often public domain), other titles printed on-demand, and wiki-based material.* Bradley et al. (2011) state that non-traditional prints include also books whose authors choose to publish their own material (so-called self-published books).

[16]More information about LC can be found on `https://www.loc.gov/about/`.

TECH97 series.[17]

The advantage of using MARC records-based indicators is that the MARC database contains more titles than the Bowker's counts, while its greater granularity allows the researcher to decide which subcategories to include in the indicators, and thus to create less noisy indices. On the other hand, these indicators also have their weaknesses. One of them is that more recent data cannot be used because of LC's large backlog of uncatalogued titles, which may create biases. This is the reason why Alexopoulos (2011) and Alexopoulos and Cohen (2011) use only the sample for the period 1955-1997, even though they had data up to 2004. Another issue is that, similarly to Bowker's indicators, these indices can only be constructed at annual frequency due to data availability. Moreover, depending on the LC's cataloging rules some titles may be disregarded, as it is the case of self-published materials that are not eligible for cataloging because they are not produced by a recognized publisher (Holley (2014)).

To address some of these issues related to the MARC records-based indicators, Alexopoulos and Cohen (2011) construct also a quarterly indicator for computer technologies based on the titles available on Amazon for the period 1980Q1-2008Q3. Amazon is the largest book retailer in the world, its virtual bookshelves containing more than 3.4 million books at any given time (Farfan (2017)). Amazon not only has the largest and diverse collection of titles (i.e. traditional and non-traditional books, prints and ebooks), but it also has an up-to-date database given that it cannot sell materials which are not recorded and cataloged. Using Amazon's database for making an indicator has several advantages. One is that the indicator can be constructed at quarterly frequency. Moreover, as opposed to the Bowker- or MARC records-based indices, this indicator has better chances of containing most of the titles published on a given topic, and hence best reflect the reality.[18] However, the Amazon-based indicator has also some limitations. Alexopoulos and Cohen (2011) mention the fact that classification of titles is done by Amazon's employees and while there is no reason to assume there is something wrong with their classification, the grouping is not granular enough to allow the researcher to choose which subcategories to include in the index. For this reason, Alexopoulos and Cohen (2011) consider this index noisier than the MARC records-based indicator. Another drawback is the shorter timespan of this series. Because the backward reach of Amazon's titles is limited to 1980, it is not possible to use this series for the purpose of the present paper.

While having the potential of being valuable proxies for technological change, all the book-based indicators used so far in the literature have the drawback of being left to the discretion of either the cataloging institution, or the researcher. As seen in the discussion above, depending on the institutions' policies or researcher's preferences, the counts of

[17]Details concerning the data source are presented in Appendix A.

[18]Alexopoulos and Cohen (2011) do not explain how the Amazon-based indicator for computer technologies is constructed. In particular, they do not state if they excluded any titles depending on whether the books were self-published, or ebooks. Given that, I assume the indicator contains all titles available on Amazon on the chosen topic.

titles on specific topics may be biased. For this reason, I believe it is important to use also a more objective proxy for technological change in the empirical analysis and I consider the technological standardization-based indicator to be a good candidate for that.

2.2 Technological standardization-based indicators

Baron and Schmidt (2014) were the first to use technology standards as an indicator of technological change for empirical research. Standardization is the process through which common rules for all producers and users of a technology are set such that compatibility is ensured. Because of that, standardization precedes the implementation of new technologies, and hence provides economic agents with information about future possible productivity gains.

Baron and Schmidt (2014) use data on standards documents from PERINORM to analyze the effect of the adoption of new technology standards on TFP and economic activity. In the revised version of the paper, Baron and Schmidt (2017) replace the data from PERINORM with the one from the Searle Center Database. The reason is that the latter is a more comprehensive source of information on technology standards from a large sample of standard setting organizations, henceforth SSOs.[19] Standards are usually developed by SSOs (i.e. established organizations, informal consortia, or interest groups), while some firms can also adopt *de facto* standards. *De facto* standards emerge from public acceptance (e.g. MP3 audio format, HTML, PDF), but are often eventually adopted by established SSOs as formal (*de jure*) technology standards. The Searle Center database includes standards established by more than 600 SSOs (formal SSOs and informal standards consortia), but excludes *de facto* standards with the exception of those that have been eventually accredited as a *de jure* standard by one of the SSOs in the sample.

Baron and Schmidt (2017) explain that technology standards are a good proxy for technological change because standardization is an essential step in the implementation of new technologies due to its key role in harmonizing technological devices and ensuring compatibility. They focus their analysis on information and communication technologies (ICT) standards, arguing that ICT has been shown to be a general purpose technology (GPT) and has constituted the dominant GPT in recent decades. The series is constructed by counting the number of industry standards released per quarter in classes 33 ("Telecommunications. Audio and video engineering") and 35 ("Information technology. Office machines") according to the international classification of standards (ICS) system. For robustness checks, Baron and Schmidt (2017) also create an indicator in which they include standards from the field of electronics.[20] Moreover, the information included in

[19] Baron and Spulber (2015) describes in details the Searle Center Database and the use of its content for empirical research.

[20] In this indicator, Baron and Schmidt (2017) add also the standards in the classes 31 ("Electronics") and 37 ("Image technology").

the Searle Center Database allows Baron and Schmidt (2017) to identify the national focus of standards, and hence create indicators based on standards released by US SSOs, as well as indices with standards released by both US and international SSOs that also apply to the US.

For the analysis in this paper, I use both technological standardization-based indicators (i.e. counts of standards on ICT and ICT plus electronics, respectively) at quarterly and annual frequency. Nevertheless, the main indicator is the one based on counts of standards on ICT and electronics, as it includes more technologies, and thus I assume it to be closer to the indicator based on Bowker's book titles in the category technology (TECH). I perform most exercises with the indicators based on the standards released by US SSOs, but I consider for robustness checks also the series obtained using standards from international SSOs. I further check the results for the case when the indicators only include new standards and no standards upgrades.[21] The data is available for the period 1949Q1-2014Q4.

The advantage of using the counts of technology standards adopted as proxy for technological change, as opposed to book titles counts, is that standardization is more regulated, and thus both the counting and classification are more objective, transparent, and consistent over time. Moreover, data is available at quarterly and annual frequency, which gives the possibility of performing more extensive analyses. However, there are some drawbacks of using this indicator. One issue is that the grouping of standards from various ICS classes is left to the discretion of the researcher. For example, Baron and Schmidt (2017) create the indicators using the counts of standards from classes 33-35 and 31-37, respectively, but one may think that some other technologies should be included in a general indicator of technological change (e.g. 71 ("Chemical technology"), or 75 ("Petroleum and related technologies")). Moreover, as Baron and Schmidt (2017) note, it might also be the case that there exists a longer time lag between standardization and adoption/commercialization of new technologies, than between the publication of new titles and adoption, which may affect the empirical results.

The other macroeconomic variables used in the estimations are: output in the business sector, hours of workers on non-farm payrolls, consumption, investment, TFP (adjusted for capacity utilization), and index of consumer sentiment from the University of Michigan. Macroeconomic aggregates are real, seasonally adjusted and in per capita terms, being divided by the population aged 16 and above. All data series are used in log levels in the empirical exercises. Quarterly data is available for the period 1955Q1-2014Q4. Annual data is available for all variables only from 1964, hence, in order to ensure comparability of results, the sample period used throughout this paper is 1964-2012. Details concerning the data construction and sources are presented in Appendix A.

[21] I am thankful to Julia Schmidt for providing me the dataset containing the various counts of standards that she uses in Baron and Schmidt (2017).

3 Comparison of Technological Change Indicators

In Figure 1, I present the annual series for the main two technological change indicators I use in this paper, the Bowker's book titles in the category technology (TECH) and the counts of standards on ICT and electronics that were released in the US (US ICT+ELEC Standards). While Bowker's series is available starting from 1955 and the counts of standards from 1949, I plot the series only from 1964 onwards since the empirical analysis is performed using annual data for the sample period 1964-2012, and hence the relationship between indicators is relevant only for this time frame.

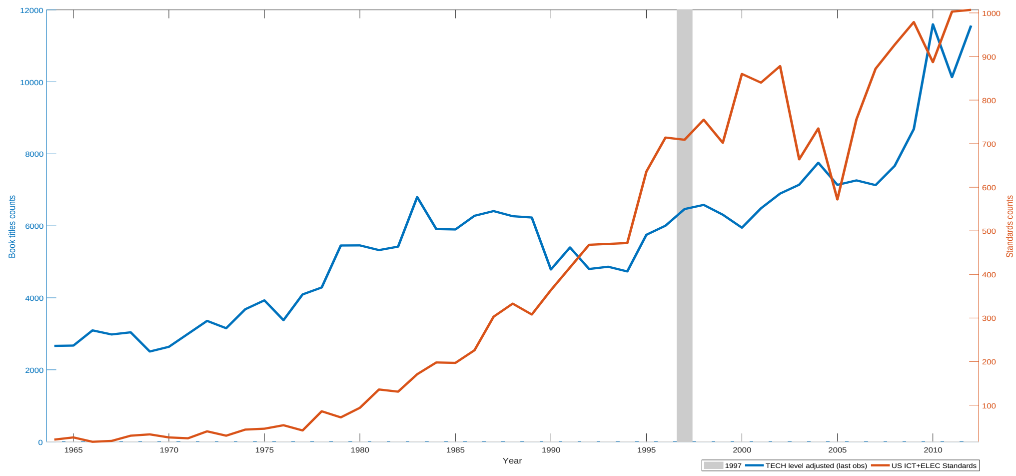

Figure 1: Comparison of the main technological change indicators for the sample period 1964-2012. The blue line represents the annual series for the Bowker's book titles in the category technology (TECH), break-adjusted level data obtained by fixing the level for the reference period to the latest available data point. The orange line defines the annual series for the counts of standards on ICT and electronics that were released in the US. The left-hand side axis corresponds to the number of book titles, while the right-hand side axis corresponds to the number of standards. The shaded area indicates the year 1997, which is the end period of the sample used in Alexopoulos (2011).

Only by eyeballing this figure one may observe that both series are upward trending. However, while the number of new titles displays a rather steady growth over time with a slight acceleration in the more recent years, the counts of standards grow more by leaps and bounds. Thus, it is hard to judge from this picture how correlated the two series are. The computation of cross correlations indicates a strong relationship between the series, but the trend in both series may give rise to this strong (maybe spurious) relation.[22] Therefore, I postpone the discussion of the importance of these two indicators

[22]The cross correlations of growth rates or detrended series indicate only a weak relationship, which may be positive or negative depending on the leads or lags considered.

and whether we can use them interchangeably, to the results section in which I present impulse responses and forecast error variance decompositions for various settings.

Moreover, in this figure I highlight the year 1997 in order to indicate the end period for the sample used in Alexopoulos (2011). As it can be observed, both series display significant fluctuations in the period between 1998 and 2012 that deserve to be considered for the empirical analysis of the impact of technological change on economic activity. In the discussion of results, I explain the differences that arise from reducing the sample that covers the period 1964-2012 to the one that only covers the period 1964-1997.[23]

Figure 12, in Appendix B, illustrates the two annual series for new titles in the category technology (TECH) for the sample period 1955-1997, which are used in Alexopoulos (2011). One is the indicator based on Bowker's book titles in the category technology (TECH97), while the other is the MARC records-based indicator for the field of technology (TECH2). Even though TECH2 is by construction a more exhaustive indicator of technological change than TECH97 because it includes more titles, the two series seem to follow a common growth path until the early 1980s, when they start to slightly diverge. For this reason, in the exercises performed with the shorter sample, I also check the robustness of results when TECH97 is replaced by TECH2.

In Appendix C, I display the annual series for various technological standardization-based indicators.[24] In Figure 13, I plot the baseline series, which is the indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards), against the series that contains only the counts of new standards on ICT and electronics, and thus excludes any updated standards (US ICT+ELEC New Standards). Until late 1980s the series almost coincide, which implies that most of the standards developed were new ones. Afterwards, the gap between the series becomes larger, indicating that in the recent years many standards were not new, but updates of previously released standards. While I assume that a technology of the early 90s is not the same with the updated technology of today, and thus the original and the updated standards for this technology should not be considered the same, I also perform robustness checks with the indicator based only on new standards.

Figure 14, Appendix C, illustrates the comparison between the baseline indicator (US ICT+ELEC Standards) and the indicator based only on counts of standards on ICT (US ICT Standards). Lastly, Figure 15 compares the indicators based on the counts of standards on ICT that were released in the US (US ICT Standards) and those released in the US and abroad (US+Int ICT Standards). Baron and Schmidt (2017) argue that the three series are positively correlated, with the relationship being stronger between the baseline indicator (US ICT+ELEC Standards) and the indicator based only on counts

[23] Alexopoulos (2011) considers the sample 1955-1997, but not all data series in my sample are available starting from 1955.

[24] The plots for the quarterly series look similar and are not included in this paper. However, for the sample period 1975Q1-2011Q4, they are illustrated in Baron and Schmidt (2017).

of standards on ICT (US ICT Standards).[25] Among these series, Baron and Schmidt (2017) choose the indicator based only on counts of standards on ICT released in the US (US ICT Standards) to be their baseline indicator, with the motivation that ICT is the most dominant general purpose technology (GPT) of the recent decades. In this paper, I prefer to use instead the indicator based on counts of all standards on ICT and electronics released in the US as baseline indicator because it is a more comprehensive index, but I use the other indicators for robustness checks.

4 Empirical Approach

I estimate a linear vector autoregressive (VAR) model, which is given by:

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \epsilon_t,$$

where Y_t is a vector of k endogenous variables modeled as the sum of an intercept c, p lags of the same endogenous variables and $\epsilon_t \sim WN(0, \Sigma)$, which is a vector of reduced-form residuals with mean zero and constant variance-covariance matrix, Σ. Φ_i are the matrices containing the VAR coefficients. As a general rule, the system with quarterly data features four lags, while the model with annual data has two lags.[26]

The variables in Y_t are log-levels and most of them are also integrated. Nevertheless, I choose to estimate the VAR model in levels and do not assume a specific cointegrating relationship between the variables. This is the approach taken in the empirical news literature with the motivation that by estimating the model in levels it is possible to keep the information contained in the long-run relationships. Moreover, this estimation is shown to be robust to cointegration of unknown form and gives consistent estimates of the impulse responses.[27] Given that the purpose of this paper is to compare the results obtained in models that comprise technological change indicators with those in the empirical news literature, I keep the modeling assumptions imposed in this literature.

The reduced-form residuals can be written as a linear combination of the structural shocks $\epsilon_t = Au_t$, assuming that A is nonsingular. Structural shocks are white noise distributed $u_t \sim WN(0, I_m)$ and the covariance matrix is normalized to the identity matrix. To identify the structural shocks from the reduced-form innovations, $k(k-1)/2$ additional restrictions on A are needed. Following the news literature, I consider two identification schemes. The first is based on short-run restrictions, while the other on medium-run restrictions. The goal is to identify two productivity shocks, an unanticipated productivity shock and an anticipated (news) shock, along with a technology shock.

[25] Based on my computations, results hold regardless of the sample size considered.

[26] For models with annual data, sometimes the Information Criteria indicate the use of more or less lags. I discuss these issues throughout the paper whenever it is the case.

[27] An extensive discussion of this issue is done in Bolboaca and Fischer (2017b).

The short-run identification scheme is applied as it follows. The innovations are orthogonalized by decomposing the variance-covariance matrix Σ of the reduced-form shocks into the product of a lower triangular matrix A and its transpose A' ($\Sigma = AA'$). The first three shocks are defined as the unanticipated productivity shock, the technology shock, and the news shock. In systems with more than three variables, the other shocks cannot be economically interpreted without imposing additional restrictions.

Bolboaca and Fischer (2017b) argue that the unanticipated productivity shock can be thought of as an unexpected improvement in productivity due to sudden changes in policies or management practices that promote more production. This shock is identified with short-run zero restrictions under the assumption that TFP is on the first position in the system of variables and the unanticipated productivity shock is the only shock having an immediate effect on it. The second variable included in the system is the technological change indicator. The other shock on this variable, in addition to the unanticipated productivity shock, is defined to be the technology shock. The third variable has to be one that contains significant information about new technologies with great potential to increase productivity in the future. Beaudry and Portier (2006) were the first to introduce this concept and used stock prices as the informative variable about future changes in productivity.[28] Bolboaca and Fischer (2017b) advise to use the index of consumer sentiment instead of stock prices as it contains more stable information about future productivity growth. Consequently, I put the index of consumer sentiment on the third position of the system. The shock on this variable, in addition to the unanticipated productivity shock and the technology shock, is defined to be the news shock.

The second identification scheme imposes medium-run restrictions in the sense of Uhlig (2004).[29] As in the previous case, the unanticipated productivity shock is the only shock affecting TFP on impact. The news shock is then identified as the shock that has no immediate effect on TFP and that, in adition to the unanticipated productivity shock, influences TFP the most in the medium-run. More precisely, it is the shock which explains the largest share of the TFP's forecast error variance (FEV) at some specified horizon h.

Innovations are orthogonalized by applying the Cholesky decomposition to the covariance matrix of the residuals, Σ. The entire space of permissible impact matrices can be written as $\tilde{A}D$, where D is a $k \times k$ orthonormal matrix ($DD' = I$). The h step ahead

[28] Barsky and Sims (2012) and Ramey (2016) argue that stock prices may not be the best variable to be used in this setting because they are very volatile and prone to react to many other forces.

[29] The first to apply medium-run restrictions to identify news shocks were Barsky and Sims (2011). The method I use in this paper to identify news shocks was introduced by Beaudry et al. (2011). This approach differs from the original one of Barsky and Sims (2011) because the latter aims at identifying a shock with no immediate effect on TFP that maximizes the sum of contributions to TFP's FEV over all horizons up to the truncation horizon H. Bolboaca and Fischer (2017b) show that the news shock identified with the method of Barsky and Sims (2011) is contaminated with contemporaneous effects, being a mixture of shocks that have either permanent or temporary effects on TFP.

forecast error is defined as the difference between the realization of Y_{t+h} and the minimum mean squared error (MSE) predictor for horizon h:[30]

$$Y_{t+h} - P_{t-1}Y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A} D u_{t+h-\tau}$$

The share of the forecast error variance of variable j attributable to structural shock i at horizon h is then:

$$\Xi_{j,i}(h) = \frac{e_j' \left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_i e_i' \tilde{A}' D B_\tau' \right) e_j}{e_j' \left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau' \right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} \tilde{A} \gamma \gamma' \tilde{A}' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'},$$

where e_i denote selection vectors with the ith place equal to 1 and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the ith column of D, which will be denoted by γ. $\tilde{A}\gamma$ is a $m \times 1$ vector and has the interpretation as an impulse vector. The selection vectors outside the parentheses in both numerator and denominator pick out the jth row of the matrix of moving average coefficients, which is denoted by $B_{j,\tau}$.

Note that TFP is on the first position in the system of variables and let the unanticipated productivity shock be indexed by 1 and the news shock by 2. Having the unanticipated shock identified with the short-run zero restrictions, I identify the news shock by choosing the impact matrix to maximize contributions to $\Xi_{1,2}(h)$ at h=40 quarters, or h=80 quarters.

When I employ annual data, I investigate these shocks in settings which include, apart from TFP, the technological change indicator, and the index of consumer sentiment, either hours worked, consumption, output or investment as a fourth variable. In several applications, I also consider the three variables model. Given the limited number of observations in the sample with annual data, I do not consider larger settings. However, Bolboaca and Fischer (2017b) encourage the use of larger settings for the robustness of results and for this reason, when using quarterly data, I work with a system that contains all seven variables.

With both identification schemes, I allow the unanticipated productivity shock to have an immediate effect on all variables. On the other hand, the technology shock has an immediate effect on the technological change indicator and the other variables of the model, but TFP responds with a lag. This approach is different from the one of Alexopoulos (2011) and Baron and Schmidt (2017), who place the technological change indicators on the last position of the system. The reason is that they want all macroeconomic variables to respond with a lag to a technology shock.[31] However, following the empirical news literature, I consider that a technology shock provides economic agents with information about the future potential productivity gains, which may encourage

[30]The minimum MSE predictor for forecast horizon h at time $t-1$ is the conditional expectation.

[31]Alexopoulos (2011) claims that the ordering of the variables do not influence her results.

them to respond immediately in order to be among the first to benefit from the adoption of the new technologies. The coordination of agents' actions may lead to an increase in consumption and investment, and consequently in output, in anticipation of the change in productivity. This view opposes the one of Baron and Schmidt (2017) who consider that macroeconomic aggregates should respond with a lag to the technology shock because of the implementation lag and slow diffusion of technology into productivity. Finally, both TFP and the technological change indicator respond with a lag to a news shock, but all other variables are allowed to react on impact.

5 Results

5.1 Results Obtained Using Bowker's Book-Based Indicators

The benchmark setting I use contains TFP adjusted for capacity utilization, the Bowker's book-based indicator for the category technology (TECH) and the index of consumer sentiment. The variables are introduced in the model in this precise order and the structural shocks are obtained from the reduced from residuals by applying the short-run identification scheme. The first shock is the unanticipated productivity shock and has an immediate effect on all three variables. The second shock, the technology shock has an immediate effect on both the book-based indicator and the confidence index, but affects TFP with a lag. The third shock has an immediate effect on the index of consumer sentiment, but not on the others, which respond with a lag. The shock on the measure of consumer confidence, unrelated to current changes in productivity, has been shown in the empirical news literature to be highly correlated with the news shock.[32] While in the related literature, this shock is obtained in models that lack a direct measure of technological change, I choose to identify it also in this setting in order to investigate how the shock on the confidence measure, henceforth news shock, and the shock on the technological change indicator, i.e. technology shock, compare. Figure 2 displays the bias corrected mean impulse responses to a one standard deviation positive technology shock. These results are obtained in the three-variables VAR model, estimated with two lags.[33] While one lag is usually considered to be sufficient for estimating a VAR with annual data, I choose to employ two lags to ensure robustness of my results given that the system potentially contains unit root or near unit root variables.[34]

The impulse responses indicate that a positive technology shock leads to a permanent increase in TFP, the effect becoming apparent already in the second period. Consumer confidence also responds positively, but the effect is not significant for the first year.

[32]Details can be found in Bolboaca and Fischer (2017b).

[33]The Akaike Information Criterion (AIC) indicates two lags, while the Bayesian Information Criterion (BIC) indicates one lag.

[34]See Kilian and Lütkepohl (2017) for details on the importance of lag augmentation in the particular case of VAR models with integrated variables.

Interestingly, the positive effect is quite persistent, lasting for about ten years after the shock hits.

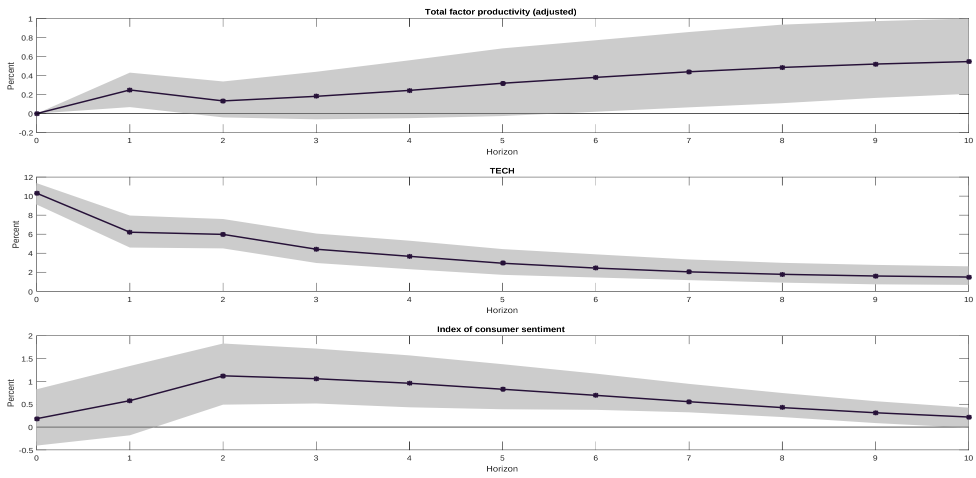

Figure 2: Impulse responses to a one standard deviation positive technology shock. The shaded area corresponds to the 68% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR. The horizontal axis indicates the forecast horizon (years) and the unit of the vertical axis is percentage points.

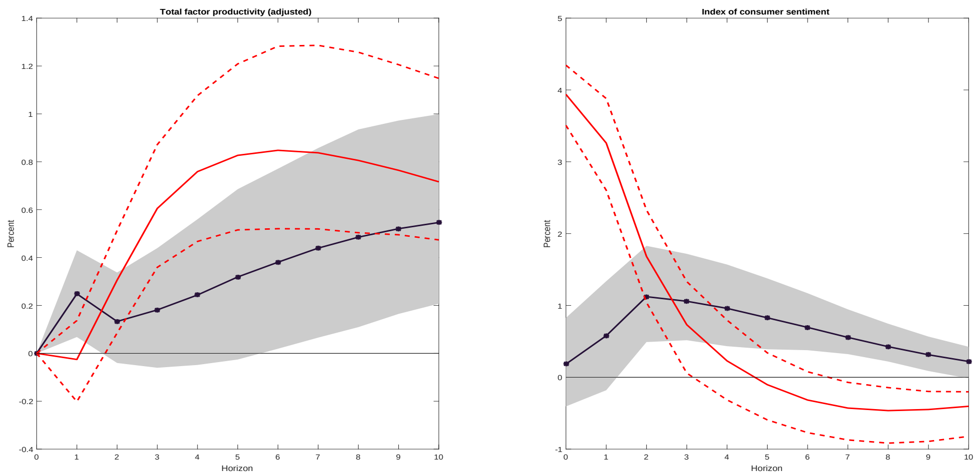

Figure 3: Comparison of the technology and news shocks. The black starred line corresponds to the impulse responses to a technology shock. The red solid line corresponds to the impulse responses to a news shock. The shaded area corresponds to the 68% confidence intervals for the responses to the technology shock, while the dotted red lines define the equivalent for the responses to the news shock. The unit of the horizontal axis is years and of the vertical axis is percentage points.

In Figure 3, I compare the effects of the technology shock to those of the news shock on TFP. It is evident that the responses to the two shocks are not significantly different from each other. While the news shock does not seem to affect productivity for the first two years after the shock hits, its effect becomes significantly positive afterwards and permanent. The mean impulse responses of TFP to the two shocks do not look similar. However, the confidence bands overlap, which indicates that there are no significant differences between the two. In contrast, the effect of the news shock on the index of consumer sentiment is very different from the one of the technology shock. Consumer confidence increases immediately after the positive news shock hits, but the effect fades away fast.

The effects of both shocks on macroeconomic variables are presented in Figure 4. These impulse responses are obtained after estimating four-variables VAR models in which each of the variables is included as the forth.[35] The impulse responses indicate a positive instantaneous effect of the technology shock on all variables. All four variables continue increasing after the shock hits, which indicates that they not only anticipate the increase in productivity but also track the diffusion of the new technologies. At a horizon of ten years, output, investment, and consumption seem to stabilize at a new permanent level, while the effect on hours worked starts diminishing. In contrast, the impulse responses to the news shock indicate significantly stronger positive immediate effects of the news shock on the macroeconomic variables. All four responses display hump-shapes and clearly indicate that the effects of the news shock are less persistent than those of the technology shock. The effects on most variables, with the exception of output, seem to fade away after ten years. To conclude, from the comparison of the impulse responses to these two shocks, I observe that both shocks have small or insignificant effects on TFP in the short-run, but lead to higher long-run levels of productivity. Both shocks lead also to a comovement of macro aggregates, with output, consumption, investment, and hours worked, increasing on impact. However, the dynamics of the macroeconomic variables are not the same following the two shocks.

In Figure 16, Appendix D, I present the impulse response functions to the unanticipated productivity shock. This shock is defined as the only shock with immediate effect on TFP, while all the other variables of the model are allowed to respond instantaneously to it. For brevity, I do not make a discussion of all these impulses and do not use them in the comparison of results. However, I consider some results worth mentioning. Firstly, the effect of the unanticipated productivity shock on TFP is persistent, but transitory. The immediate effects on most macroeconomic variables are not significantly different from zero. In contrast, hours worked decrease on impact following the unanticipated

[35] The models are estimated with two lags. The AIC indicates two lags for the models with output, or consumption, as the forth variable, one for the model with investment and four for the model with hours. There are no significant differences in the results when I change the number of lags to those indicated by AIC.

productivity shock, which is in line with the results obtained in the related literature.[36] Moreover, the dynamics of most variables are also in accordance with the findings in the related literature, with the exception of consumption, for which the effect of the unanticipated productivity shock seems to be persistently negative in the long-run.

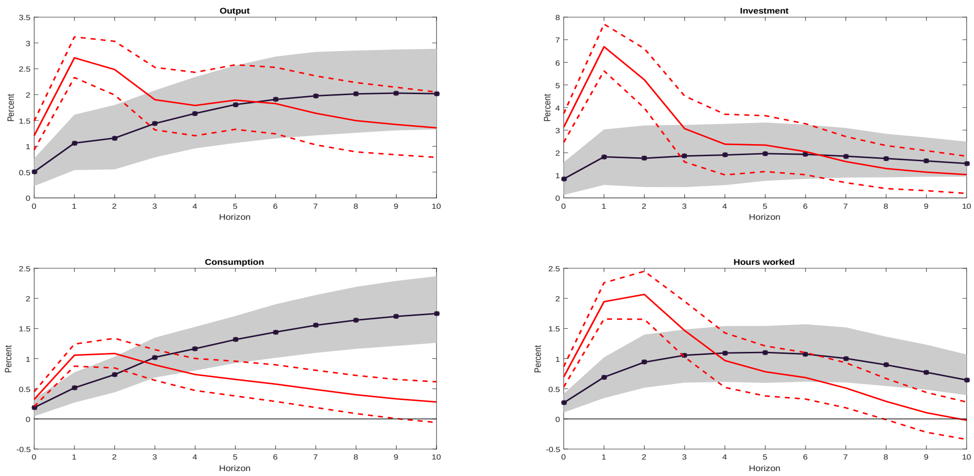

Figure 4: Comparison of the technology and news shocks. The black starred line corresponds to the impulse responses to a technology shock. The red solid line corresponds to the impulse responses to a news shock. The shaded area corresponds to the 68% confidence intervals for the responses to the technology shock, while the dotted red lines define the equivalent for the responses to the news shock. The unit of the horizontal axis is years and of the vertical axis is percentage points.

In Table 1, I present the contribution of the unanticipated productivity shock, the technology shock and the news shock, to the FEV of TFP and the index of consumer sentiment.[37] As expected, the unanticipated productivity shock explains the biggest share of the variation in TFP at all forecast horizons. However, the news shock explains about 20 percent of the variation in TFP in the medium- and long-term. An interesting result is the percent of variation of TFP that can be attributed to the technology shock. The share is quite small in the short-run, but it starts increasing in the medium-run, being above 10 percent at a horizon of ten years and almost 32 percent at a horizon of thirty years. What is even more intriguing is that, while the news shock contributes most to the variation of TFP at a horizon of ten years, the contribution of the technology shock continues to increase with the forecast horizon.

[36]See, for example, Galí (1999) and Basu et al. (2006).

[37]The shares displayed in the table are the average of the contributions obtained in the three-variables VAR model (TFP, TECH, index of consumer sentiment) and in the four-variables VAR models with output, consumption, investment, or hours worked as the forth variable. The shares obtained in each of these models can be provided by the author.

Table 1: Forecast Error Variance Decomposition of TFP and ICS. The numbers indicate the percent of the FEV of TFP and ICS explained by the unanticipated productivity, technology and news shocks at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
Unanticipated productivity shock	97.38	70.78	62.86	46.84	43.05
Technology shock	1.82	6.49	10.66	26.62	31.98
News shock	0.06	21.56	24.35	21.81	19.89
Index of consumer sentiment					
Unanticipated productivity shock	8.15	14.48	14.57	14.57	14.59
Technology shock	1.69	15.68	16.65	16.76	16.79
News shock	89.52	66.88	65.76	65.50	65.44

The contributions of the technology and news shocks to the variation in macroeconomic variables are displayed in Table 2. The technology shock explains a small percent of the variation in macroeconomic variables in the short-run, while the news shock explains more than 50 percent of the variation in most variables at a horizon of two years. However, the roles are reversed when considering the lower frequencies. In the medium- to long-run, the technology shock explains more than 40 percent of the variation in output, about 34 percent of the variation in hours worked, and 17 percent of the variation in investment. A particular result is the high contribution that the technology shock has to the variation of consumption, which goes above 70 percent at a horizon of twenty years.

When replacing the book based indicator for category technology (TECH) with the indicator for category science (SCI), I do not obtain the same results. At first sight, most results hold qualitatively. In Figure 17, Appendix D, I present the impulse responses to a one standard deviation positive technology shock (on variable SCI). These results are obtained in the three-variables VAR model, estimated with two lags, in which variable TECH is replaced by SCI. The impulse responses indicate that a positive technology shock leads to a permanent increase in TFP. In contrast to the shock on TECH, the response of consumer confidence is not significantly different from zero at all horizons. Moreover, in Figure 18, Appendix D, it is evident that the effects on most macroeconomic variables are not significant, either on impact or at longer horizons. This indicates that the counts of new titles in category science cannot be used as an indicator for technological change instead of the counts of books in category technology.

As a final step in the analysis of results obtained using the book-based indicators, I wish to draw a parallel between these results and those obtained in Alexopoulos (2011). While the results I find in this paper are qualitatively in line with those of Alexopoulos (2011), there are several differences in our approaches. As I previously stated, we choose to place the indicator of technological change on different positions in the VAR. While I set it on the second position, Alexopoulos (2011) puts it last in the system of variables. This gives the difference in the immediate responses of the variables in the model to the technology shock. With my approach, which follows the one in the empirical news literature, except for TFP, the other variables are allowed to respond on impact to the technology shock. In Alexopoulos (2011), all variables respond with a lag to this shock. My findings indicate that all macroeconomic variables respond significantly on impact to the technology shock, and hence I do not see a reason for imposing these 'no immediate response' restrictions.

Table 2: Forecast Error Variance Decomposition of macro variables. The numbers indicate the percent of the FEV of output, consumption, investment, and hours worked explained by the technology shock and the news shock at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Output					
Technology shock	9.74	28.23	32.49	41.94	44.67
News shock	61.86	48.47	43.78	34.03	31.43
Consumption					
Technology shock	12.03	48.5	55.31	73.46	79.55
News shock	48.68	24.31	18.44	8.59	6.35
Investment					
Technology shock	4.51	12.28	14.06	16.79	17.36
News shock	61.33	53.37	51.13	45.54	43.36
Hours worked					
Technology shock	7.6	28.95	32.51	34.06	33.82
News shock	58.71	52.6	49.72	47.36	46.78

Another difference consists in the sample used for the empirical analysis. Alexopoulos (2011) uses data for the sample period 1955-1997, while the data employed in this paper covers the period 1964-2012. For comparison, I present in Figure 19, and Figure 20, in Appendix D, the impulses responses to the technology shock when the Bowker's book based indicator for category technology (TECH97) is used. For this analysis, I consider the subsample for the period 1964-1997.[38] Both Alexopoulos (2011) and I estimate a linear VAR model with data in log-levels. However, Alexopoulos (2011) includes one lag of the endogenous variables and a linear time trend in the model.[39] In contrast, I

[38]At annual frequency, not all time series in my sample are available starting from 1955. While I cannot use the exact sample period as in Alexopoulos (2011) for all estimations, I could perform the analysis for a bivariate model with only TFP and the technological change indicator and the findings were very similar.

[39] Alexopoulos (2011) uses the BIC to decide upon the lag length and includes a time trend to hopefully

choose a lag length of two. The choice is in several settings indicated by the AIC, the information criterion advised to be used in case of small sample size,[40] while in others I choose it for consistency and robustness.[41] The impulse responses displayed in Figure 19, and Figure 20, Appendix D, indicate that using the shorter sample does not significantly influence the results. The technology shock leads to a permanent increase in TFP and the comovement of macroeconomic variables. However, the confidence bands are wider and this makes the persistence of the effects arguable. As the increase in the width of confidence bands may be the side-effect of estimating the VAR model with two lags and using a shorter sample, I focus on the mean impulse responses to make my argument and these are qualitatively similar to those obtained with the larger sample.

Moreover, in Figure 19, and Figure 20, in Appendix D, I also present the impulse responses obtained when the Bowker's book-based indicator is replaced by the MARC records-based indicator, both for the titles published in the category technology. The results indicate that the two technological change indicators can be used interchangeably as the effects of the two technology shocks are virtually the same on almost all variables, with the exception of consumption, on which the technology shock obtained using the MARC records-based indicator has a significantly smaller effect.

A last (possible) difference to the approach in Alexopoulos (2011) is that we might use different measures of productivity.[42] We both use the series constructed with the method of Fernald (2014) based on Basu et al. (2013) and Basu et al. (2006), but I perform the analysis using the TFP series that is adjusted for variations in capacity utilization. It is not clear to me whether the TFP series used by Alexopoulos (2011) is the same, or the one which is unadjusted for capacity utilization. I checked the robustness of results when the TFP series unadjusted for capacity utilization is used and the differences are mostly quantitative. The impulse responses obtained with the unadjusted series usually indicate stronger effects of the technology shock, mainly in the short-run. However, the use of the TFP series that is unadjusted for capacity utilization is not recommended in this setting because capacity utilization may also respond to the technology shock, as firms may decide to increase capacity until adopting the new technologies in order to smooth output production. Thus, the response of TFP to the technology shock may reflect the increase in capacity and not the diffusion of technologies in the short-run.

To conclude, using the the book-based indicators of Alexopoulos (2011) as a proxy for technological change I find that technology shocks lead to a comovement of macro aggregates and explain a big share of the variation in these variables in the medium-

address the problem of estimating a model with level data, which may be (co-)integrated.

[40]See Liew (2004) for details on the choice of information criteria depending on the sample size.

[41]Kilian and Lütkepohl (2017) explain that the lag augmentation of VAR models with potentially integrated variables can ensure robustness of results, but may involve a loss of efficiency in estimation, reducing the power of tests and inflating the width of confidence intervals.

[42]Even if the measure is the same, we definitely use different vintages of the TFP series, as I employ the latest available vintage as of October 2017.

to long-run. Technology shocks are more similar to news shocks than to unanticipated productivity shock. However, while the technology and news shocks have qualitatively similar effect on macroeconomic variables, there are significant quantitative differences. The effects of the news shock are stronger in the short-run, but they diminish in the medium- to long-run.

5.2 Results Obtained Using Standards-Based Indicators

In this section, I perform a similar analysis of technology shocks, but in this setting I use standards-based indicators as proxy for technological change. The benchmark setting I use contains TFP adjusted for capacity utilization, the counts of standards on ICT and electronics that were released in the US (US ICT+ELEC Standards) and the index of consumer sentiment. The variables are introduced in the model in this precise orde, and the structural shocks are obtained from the reduced from residuals by applying the short-run identification scheme. As before, the first shock is the unanticipated productivity shock, the second is the technology shock, and the third is the news shock. The three-variables VAR model is estimated with two lags.[43]

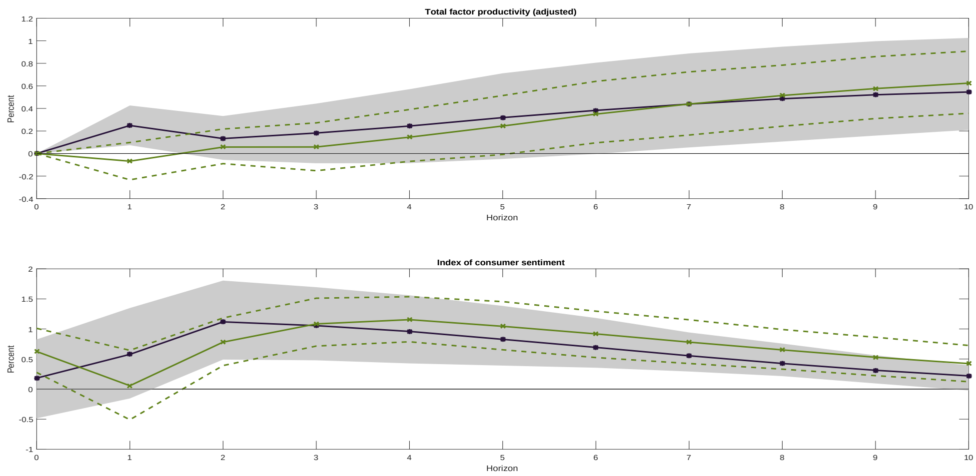

Figure 5: Comparison of technology shocks. The black starred line defines the impulse responses to a technology shock on variable TECH and the shaded area is the corresponding 68% confidence interval. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards and the dotted green lines define the corresponding 68% confidence interval. The unit of the horizontal axis is years and of the vertical axis is percentage points.

Figure 5 displays the bias corrected mean impulse responses to one standard deviation positive technology shocks. I present the results for the technology shock obtained in this setting, in which I use the standards-based indicator US ICT-ELEC Standards as

[43]The AIC indicates three lags, while the BIC indicates one lag.

proxy for technological change, to those obtained in the previous analysis, in which I employed the book-based indicator TECH instead. The impulse responses indicate that a positive technology shock, on the standards-based indicator, leads to a permanent increase in TFP, but the effect is significant only after about five years. Consumer confidence responds positively already on impact, but the effect is not significant for the first year. Interestingly, I find the same persistent positive effect of both technology shocks on the confidence measure. Moreover, apart from the effect on TFP in the first year, the two shocks seem to lead to the same dynamics in TFP and the index of consumer sentiment, as the confidence bands overlap. The closeness in the effects of the two shocks is evident also in Figure 6, in which I compare the responses of macroeconomic variables to the two technology shocks. These impulse responses are obtained after estimating four-variables VAR models in which each of the variables is included as the forth.[44] The technology shock, on the standards-based indicator, has smaller instantaneous and short-run effects on output and consumption. However, the confidence bands overlap, which indicates that there is no significant difference between these two technology shocks when judging from the perspective of impulse responses.

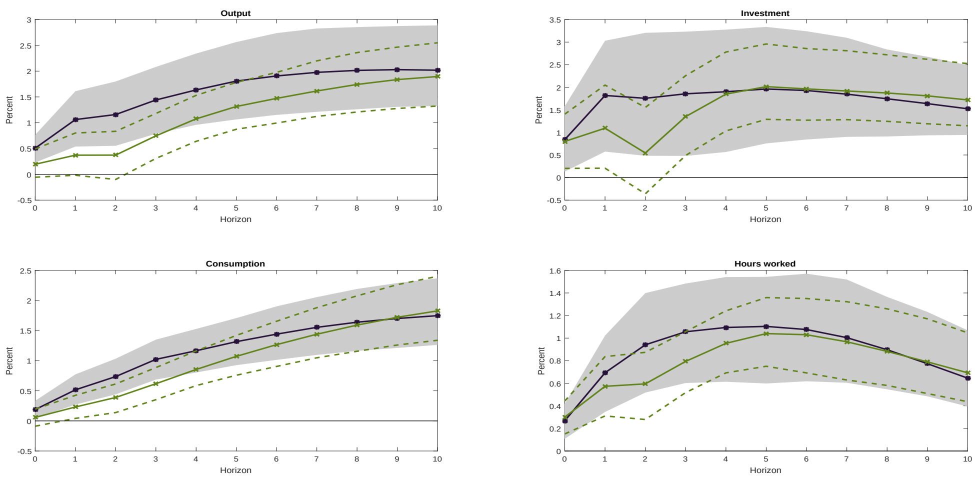

Figure 6: Comparison of technology shocks. The black starred line defines the impulse responses to a technology shock on variable TECH and the shaded area is the corresponding 68% confidence interval. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards and the dotted green lines define the corresponding 68% confidence interval. The unit of the horizontal axis is years and of the vertical axis is percentage points.

To further investigate the relationship between the two technology shock, I present in Table 3 the contribution of each of them to the FEV of TFP and the index of consumer sentiment.[45] The contributions of the technology shocks to the variation of TFP

[44]The models are estimated with two lags.

[45]The shares displayed in the table are the average of the contributions obtained in the three-variables

at different forecast horizons follow the same pattern. The shares are rather small in the short-run, but start increasing in the medium- to long-run. An interesting result is that the technology shock on variable TECH explains a bigger share of the variation in TFP at business-cycle frequencies than the technology shock on variable US ICT+ELEC Standards, but the roles are reversed at lower frequencies. Baron and Schmidt (2017) explain that the difference stems from the fact that standardization occurs prior to the introduction of books and manuals describing the technology on the market. The intuition is that publishers launch the books close to the commercialization of products using the new technology in order to sell more. In contrast, standardization precedes the development of products that use the new technology. This is why the technology shock on the TECH variable more closely tracks the diffusion of the new technology into productivity, while the shock on standardization anticipates it. However, this argument does not clarify the reversal observed in the contributions in the medium-run. My explanation for this result is that the book-based indicator is a noisier proxy for technological change and this may downward bias the effect of important technologies on economic activity. Lastly, it is important to note that when looking at the percent of variation of the confidence measure that can be attributed to the technology shocks, it is evident that the shares are close at all forecast horizons.

Table 3: Forecast Error Variance Decomposition of TFP and ICS. The numbers indicate the percent of the FEV of TFP and ICS explained by the technology shock on variable TECH, and the technology shock on variable US ICT+ELEC Standards, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
Technology shock (TECH)	1.82	6.49	10.66	26.62	31.98
Technology shock (Standards)	0.50	2.41	5.49	34.12	48.57
Index of consumer sentiment					
Technology shock (TECH)	1.69	15.68	16.65	16.76	16.79
Technology shock (Standards)	1.99	17.04	18.89	20.09	20.12

The contributions of the technology shocks to the variation in macroeconomic variables are displayed in Table 4. As seen already in the case of TFP, both technology shocks explain a small percent of the variation in macroeconomic variables in the short-run, but at these high frequencies the technology shock on variable TECH has bigger contributions. On the other hand, in the medium- to long-run the technology shock on

VAR model (TFP, technological change indicator, index of consumer sentiment) and in the four-variables VAR models with output, consumption, investment, or hours worked as the forth variable. The shares obtained in each of these models can be provided by the author.

variable US ICT+ELEC Standards explains between 28 percent and 92 percent of the variation in macroeconomic variables, and thus seems to be a more important source of macroeconomic fluctuations.

In Table 6, Appendix E, I present the contributions of the unanticipated productivity shock, the technology shock on variable US ICT+ELEC Standards, and the news shock, to the FEV of TFP and the index of consumer sentiment. The conclusions to be drawn are similar to those for the setting in which the book-based indicator was used as proxy for technological change. The only major difference consists in the contributions to the fluctuations of TFP. The unanticipated productivity shock explains the biggest share of the variation in TFP at business cycle frequencies. However, in the medium- to long-run, the technology shock becomes more important, as it explains more than 48 percent of the variation in TFP at a forecast horizon of thirty years, while the unanticipated shock explains less than 37 percent.

The contributions of the technology and news shocks to the variation in macroeconomic variables are displayed in Table 7, Appendix E. Once more, the observations are very similar. The news shock explains about 50 percent of the variation in most variables at a horizon of two years, but the contributions drop at lower frequencies. In contrast, the technology shock explains a small percent of the variation in macroeconomic variables in the short-run, while in the medium- to long-run, it becomes a major source of macroeconomic fluctuations.

Table 4: Forecast Error Variance Decomposition of macro variables. The numbers indicate the percent of the FEV of output, consumption, investment, and hours worked explained by the technology shock on variable TECH and the technology shock on variable US ICT+ELEC Standards, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Output					
Technology shock (TECH)	9.74	28.23	32.49	41.94	44.67
Technology shock (Standards)	1.49	25.4	36.71	65.65	73.89
Consumption					
Technology shock (TECH)	12.03	48.5	55.31	73.46	79.55
Technology shock (Standards)	2.58	48.08	62.45	87.69	91.32
Investment					
Technology shock (TECH)	4.51	12.28	14.06	16.79	17.36
Technology shock (Standards)	2.48	15.01	18.96	27.87	31.46
Hours worked					
Technology shock (TECH)	7.6	28.95	32.51	34.06	33.82
Technology shock (Standards)	8.3	18.97	35.76	37.16	37.39

In the analysis presented so far I use the technological change indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards). As a robustness check, I perform the same empirical exercises, but I replace the baseline indicator with one of the following: the counts of new standards on ICT and electronics, excluding any updated standards (US ICT+ELEC New Standards), the counts of standards on ICT (US ICT Standards) only and the counts of standards on ICT released in the US and abroad (US+Int ICT Standards). In Figure 21, Appendix E, I present the impulse responses of TFP, the index of consumer sentiment, output, consumption, investment, and hours worked, to the various technology shocks. The results indicate that the baseline indicator and the indicator based on counts of only new standards on ICT and electronics can be used interchangeably as the mean impulse responses almost coincide. The impulse responses to the technology shock identified using the counts of standards on ICT (US ICT Standards) lie within the confidence bands of the baseline setting, with the exception of the short-run response of investment, which is not significantly different from zero in this case. A similar conclusion can be drawn for the technology shock obtained using the counts of standards on ICT released in the US and abroad. Most impulse responses to this shock lie also within the confidence bands of the baseline setting, with only the response of consumption being entirely outside the confidence interval and indicating an insignificant effect of the technology shock on this variable. To conclude, the baseline indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards) seems to give the most robust results among the standards-based indicators I investigated. Moreover, as seen in the comparison with the Bowker's book-based indicator for category technology, the two proxies for technological change deliver similar results in terms of impulse responses and shares of variation attributed to the technology shock they help identify. Based on these findings, I infer that the indicator based on counts of all standards on ICT and electronics (US ICT+ELEC Standards) is a robust proxy for technological change. Hence, I further use the quarterly series of this indicator constructed by Baron and Schmidt (2017) to perform several empirical exercises of the news literature.

I begin by estimating a seven-variables VAR model, which contains TFP adjusted for capacity utilization, the indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards), the index of consumer sentiment, investment, hours worked, output, and consumption. The variables are introduced in the model in this precise order and the structural shocks are obtained from the reduced from residuals by applying short-run restrictions. The first shock is the unanticipated productivity shock and has an immediate effect on all variables. The second shock, the technology shock has an immediate effect on all variables, with the exception of TFP that responds with a lag. The third shock has an immediate effect on the index of consumer sentiment and the other macroeconomic variables, but TFP and the standards-based indicator are affected with a lag. I consider the same sample period as in the exercises with annual data, i.e. 1964Q1-2012Q4, in order to have comparable results.[46] The model is estimated using quarterly data, with four lags. The choice of the lag length is motivated by the usual practice in the literature, and thus by obtaining results that can be compared with those in the empirical news literature. However, as it can be observed in Figure 22, Appendix E, results do not change significantly if the estimation is performed with eight lags. The differences in impulse responses are evident only in the short-run. The results obtained in the model with eight lags indicate an insignificant effect of the technology shock on investment, output, and hours worked for the first two years and on TFP for the first almost six years. In contrast, the effects obtained in the model with four lags become significantly positive at shorter horizons. Increasing the number of lags to twelve, as it is done in Baron and Schmidt (2017), leads to a higher uncertainty of the estimates and makes the impulse responses statistically insignificant at longer horizons, but the results are still qualitatively similar.

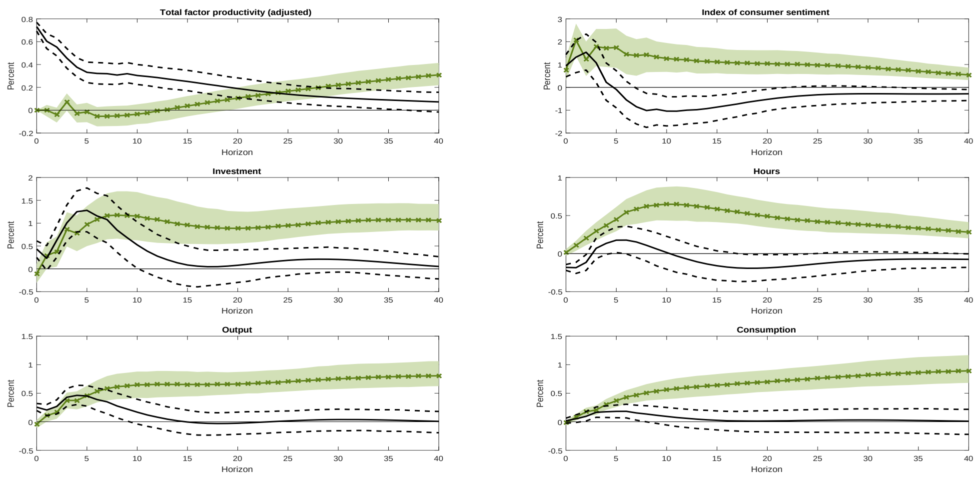

Figure 7: Comparison between the technology shock and the unanticipated productivity shock. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards and the shaded area is the corresponding 68% confidence interval. The black solid line represents the impulse responses to an unanticipated productivity shock and the dotted black lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters and of the vertical axis is percentage points.

In Figure 7, I compare the impulse responses to the technology shock with those to the unanticipated productivity shock. In response to a one standard deviation positive unanticipated productivity shock, TFP rises on impact, but the effect fades over time even though it is quite persistent. The shock has positive immediate effects also on the index of consumer sentiment, investment, output, while on consumption it is almost nil.

[46] Quarterly data is available for the period 1955Q1-2014Q4, and results do not change considerably if the whole sample is used.

However, the immediate effect on hours worked is significantly negative, which confirms the results of Galí (1999) and Basu et al. (2006). In the short-run, it is evident a hump-shaped pattern in the responses of the index of consumer sentiment, output, consumption, investment, and hours worked, but the effects wane after two to three years. Concerning the responses to the technology shock, TFP is restricted not to respond on impact, but in the first four to five years there is almost no change in its response. However, TFP starts increasing afterwards and after about fifteen to twenty years it stabilizes at a new long-run level.[47] While I do not impose any restrictions for the immediate effect on the other model variables as in Alexopoulos (2011), and Baron and Schmidt (2017), I do not find a significant impact effect of the technology shock on output, investment, consumption, and hours worked. Nevertheless, these variables start responding positively to the shock soon after the shock hits and increase for several quarters until they stabilize at higher new permanent levels. The reactions of hours worked and investment display a hump-shaped pattern in the short-run. When comparing the two shocks through the impulse response functions, I observe that the technology shock has much stronger short- and medium-run effects on all macroeconomic variables than the unanticipated productivity shock.

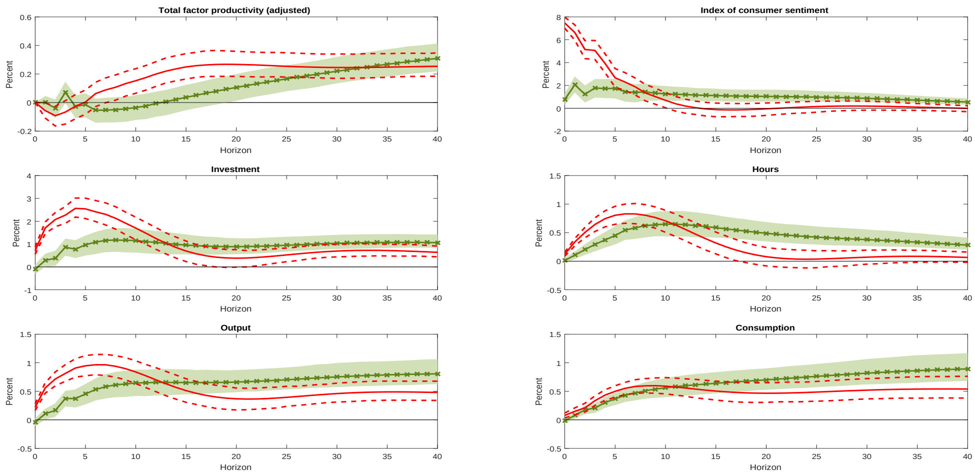

Figure 8: Comparison between the technology shock and the news shock. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards and the shaded area is the corresponding 68% confidence interval. The red solid line represents the impulse responses to a news shock and the dotted red lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters and of the vertical axis is percentage points.

In Figure 8, I compare the effects of the technology shock to those of the news shock on the model variables. The results are very similar to those obtained in the models

[47]Figure 23, Appendix E displays the impulse responses to the technology shock for forecast horizons up to 120 quarters.

with annual data. The differences between the two are mostly apparent in the short-run. The instantaneous effect of the news shock on investment, output, and hours worked is significantly higher than the one of the technology shock. Concerning the short-run dynamics, there is a hump-shaped pattern in the responses of output, consumption, investment, and hours worked to the news shock. With the exception of hours worked and the index of consumer sentiment, all variables stabilize at higher permanent levels following a news shock. However, these long-run levels are slightly lower than those reached after a technology shock hits the economy.[48]

In order to further investigate the role played by these shocks in driving macroeconomic fluctuations, in Table 5 I present the contribution of each of them to the FEV of TFP, the index of consumer sentiment, investment, hours worked, output, and consumption. The contributions of the three shocks to the variation of the model variables at different forecast horizons follow the same pattern as observed previously in the models estimated with annual data. Undoubtedly, the shares do not coincide because of the different information content of the models, but the roles of these shocks are the same at various forecast horizons. The three shocks together explain more than 60 percent of the variation in TFP at all horizons considered. The unanticipated productivity shock explains most of the fluctuations of TFP in the short-run. However, this shock does not seem to play an important role in driving macroeconomic fluctuations either in the short-run, or in the medium-run, as its contribution to the variation in macroeconomic variables is small at all forecast horizons. This contradicts the real business cycle (RBC) literature that assigns a central role to the unanticipated productivity shock in driving economic fluctuations.[49] When comparing the relative importance of the other two shocks, it is evident that the news shock plays a more important role than the technology shock at business cycle frequencies, while in the medium- to long-run the technology shock takes the lead. The news shock explains between 25 and 42 percent of the variations in macroeconomic variables at business cycle frequencies, while the technology shock explains between 27 and 42 percent of the variations in the same variables at lower frequencies. The findings for the technology shock are in line with those of Alexopoulos (2011) and Baron and Schmidt (2017), who show that technology shocks explain a small percent of the variation in macroeconomic variables in the short-run, but have bigger contributions in the medium- to long-run.

The similarity of results to those of Baron and Schmidt (2017) extends beyond the shares of the FEV attributable to the technology shock, even though we take different empirical approaches.[50] The impulse responses to the technology shock reported by Baron

[48]Figure 24, Appendix E, displays the impulse responses to the technology shock and to the news shock, for forecast horizons up to 120 quarters.

[49]The unanticipated productivity shocks are known as technology shocks in the RBC literature where aggregate productivity is affected immediately and permanently only by technology.

[50]Baron and Schmidt (2017) estimate a linear VAR with quarterly data in log-levels, but include 12 lags in the model and take a Bayesian approach for the estimation in order to use Bayesian shrinkage

and Schmidt (2017) are qualitatively similar to those I compute, with the only difference that in their paper the short-run responses of investment and output are insignificant for a longer period and TFP initially decreases following the technology shock before picking up in the medium- and long-run. I do not find a significant decrease in TFP in response to the technology shock either in the baseline model or in the settings with more lags (i.e. 8 and 12 lags).

Table 5: Forecast Error Variance Decomposition of model variables. The numbers indicate the percent of the FEV of the model's variables explained by the unanticipated productivity shock (TFP shock), the technology shock on variable US ICT+ELEC Standards, and the news shock, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
Unanticipated productivity shock	69.65	41.77	35.5	14.74	9.42
Technology shock	0.49	5.73	11.71	32.3	36.6
News Shock	1.07	19.3	21.87	19.72	16.56
Index of consumer sentiment					
Unanticipated productivity shock	3.16	5.59	5.54	5.65	5.64
Technology shock	8.51	14.38	14.89	14.95	15.07
News Shock	79.84	56.86	54.41	52.37	52.25
Output					
Unanticipated productivity shock	8.92	3.29	2.56	1.23	0.92
Technology shock	9.65	32.32	35.22	40.42	41.37
News Shock	48.54	32.48	29.02	20.36	17.49
Consumption					
Unanticipated productivity shock	3.35	0.69	0.5	0.21	0.19
Technology shock	14.89	38.36	40.39	43.31	43.52
News Shock	32.31	23.71	21.92	16.76	14.78
Investment					
Unanticipated productivity shock	9.65	6.52	5.81	4.04	3.58
Technology shock	6.62	19.81	22.86	29.64	31.2
News Shock	43.21	40.33	37.75	29.32	26.59
Hours worked					
Unanticipated productivity shock	1.82	2.24	2.17	2.37	2.39
Technology shock	10.72	27.02	27.28	27.15	27.13
News Shock	26.45	23.08	21.09	19.14	19.16

methods to tackle the problem of overparametrization. In contrast, I take a frequentist approach to estimate the model and use a lag length of 4 quarters.

The last step of my analysis is to verify how a news shock identified with the medium-run identification scheme (MRI) compares with the news shock obtained using short-run restrictions and the technology shock. The news shock identified with medium-run restrictions is defined to be the shock with no immediate effect on productivity, which explains most of the variation of TFP in the medium-run. In Figure 9, I show that the news shock obtained using medium-run restrictions, with a truncation horizon of 10 years, is virtually a mixture of the technology shock and the news shock obtained with short-run restrictions. Note that this shock is identified in the same variable setting as before, but only together with the unanticipated productivity shock. The other two shocks obtained with short-run restrictions are not identified in this framework and this allows the news shock obtained with medium-run restrictions to be a mixture of all shocks, with the exception of the unanticipated productivity shock. As it can be observed in Figure 9, the news shock identified with MRI is more similar to the news shock obtained with short-run restrictions than to the technology shock. This is confirmed also by computing the cross correlation coefficient between each pair of shocks. The correlation coefficient between the two news shocks is 0.69, while between the news shock obtained with MRI and the technology shock the coefficient equals 0.43. This is not a surprising result since in Table 5 it is evident that the news shock explains a bigger share of the FEV of TFP than the technology shock at a horizon of ten years.

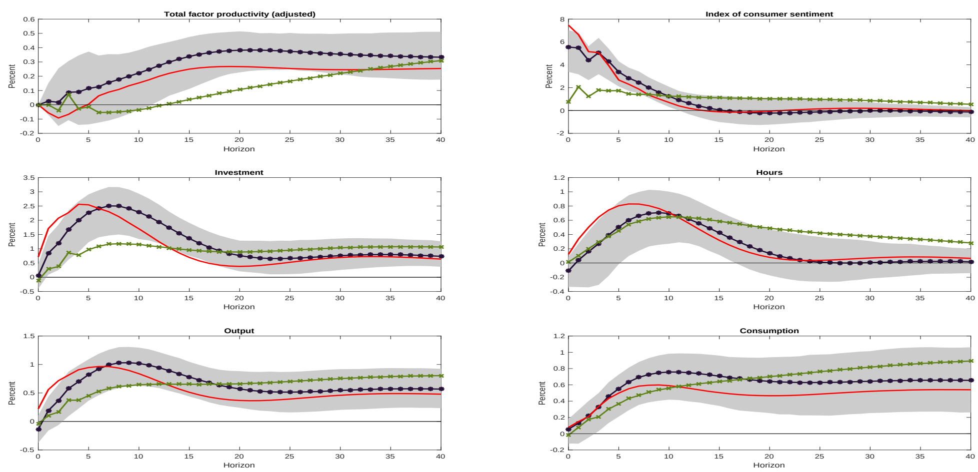

Figure 9: Comparison between the technology shock and the news shocks. The dark blue circled line defines the news shock obtained using medium-run restrictions, with a truncation horizon of 10 years. The shaded area is the corresponding 68% confidence interval. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards and the red solid line represents the impulse responses to a news shock, obtained with short-run restrictions. The unit of the horizontal axis is quarters and of the vertical axis is percentage points.

However, when comparing the news shock obtained using medium-run restrictions, with a truncation horizon of 20 years, with the other shocks (see Figure 25, Appendix E), I find that this news shock is more similar to the technology shock than to the news shock obtained with short-run restrictions. In this case, the correlation coefficient between the two news shocks is 0.45, while between the news shock obtained with MRI and the technology shock the coefficient equals 0.68. The results are reversed, which is also in line with the reversal of contributions of the two shocks to the variation of TFP at a forecast horizon of 20 years. This result confirms the conclusion of Bolboaca and Fischer (2017b) that the choice of the truncation horizon plays an important role in the identification of news shocks with MRI. With the choice of shorter truncation horizons, I find that MRI puts more emphasis on shocks that contribute more to TFP at business cycle frequencies, but with longer horizons, MRI isolates shocks that play a more important role in driving TFP fluctuations in the medium- and long-run. This is the reason why Bolboaca and Fischer (2017b) advise choosing longer truncation horizons, as this ensures obtaining more robust results.

6 Conclusions

Several approaches have been taken in the macroeconomic literature to measure the impact of technological change on economic activity. One is to apply identification schemes to identify technology shocks from macroeconomic data. The other is to use direct measures of technological change. Two recent proxies that were proposed are based on either counts of book in the field of technology, or technological standardization. The first was made by Alexopoulos (2011), who uses new book titles in the category technology as proxy for the adoption of technological innovations. The second belongs to Baron and Schmidt (2017) and is an indicator based on the counts of standards in the category ICT (and electronics). In this paper, I combine the two approaches to show which of three shocks plays a more important role for macroeconomic fluctuations: the unanticipated productivity shock, the technology shock, or the anticipated productivity (news) shock.

My findings indicate that the two technological change indicators can be used interchangeably as they give similar results. Regardless of the indicator employed, following a technology shock, TFP does not respond for several years, but then it gradually increases until it stabilizes at a new long-run level. Macroeconomic aggregates are also unaffected by the technology shock on impact, but start responding positively to the shock soon afterwards and increase for several quarters until they stabilize at higher new permanent levels. When comparing the technology shocks with the other shocks, I observe that the technology shock has much stronger short- and medium-run effects on all macroeconomic variables than the unanticipated productivity shock. The unanticipated productivity shock has positive immediate effects on almost all macroeconomic variables, with the exception of consumption on which the effect is almost nil and hours worked for which the response is significantly negative. When comparing the technology with the news shock, I find that the differences between the two shows are mostly apparent in the short-run.

An important result is that these three shocks have different roles in driving macroeconomic fluctuations, depending on the forecast horizon. The unanticipated productivity shock does not seem to play an important role in driving macroeconomic fluctuations, as its contribution to the variation in macroeconomic variables is small at all forecast horizons. When comparing the relative importance of the other two shocks, I find that the news shock plays a more important role than the technology shock at business cycle frequencies, while in the medium- to long-run the roles are reversed. For this reason, I believe it is important for future research to find what is the information that the news shock captures, apart from the development of new technologies which have been now identified through the technology shock, that leads to much stronger fluctuations in macroeconomic aggregates in the short-run than the technology shock and continues to explain a significant share of their variation also in the medium- and long-run.

References

Alexopoulos, M. (2011). Read All about It!! What Happens Following a Technology Shock? *American Economic Review*, 101 (4): 1144–79.

Alexopoulos, M. and J. Cohen (2011). Volumes of evidence: examining technical change in the last century through a new lens. *Canadian Journal of Economics*, 44 (2): 413–450.

Baron, J. and J. Schmidt (2014). *Technological Standardization, Endogenous Productivity and Transitory Dynamics*. Working papers 503. Banque de France.

— (2017). *Technological Standardization, Endogenous Productivity and Transitory Dynamics*. Mimeo. URL: `http://julia-schmidt.org/Tech_shocks_Schmidt.pdf` (visited on 09/25/2017).

Baron, J. and D. F. Spulber (2015). *Technology Standards and Standards Organizations: Introduction to the Searle Center Database*. Technical report 34. Northwestern University Pritzker School of Law.

Barsky, R.B. and E.R. Sims (2011). News Shocks and Business Cycles. *Journal of Monetary Economics*, 58 (3): 273–289.

— (2012). Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence. *American Economic Review*, 102 (4): 1343–1377.

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

Basu, S., J. Fernald, J. Fisher, and M. Kimball (2013). Sector-Specific Technical Change. *Working Paper*.

Beaudry, P. and F. Portier (2004). An Exploration into Pigou's Theory of Cycles. *Journal of Monetary Economics*, 51: 1183–1216.

— (2006). Stock Prices, News, and Economic Fluctuations. *American Economic Review*, 96 (4): 1293–1307.

— (2014). News-Driven Business Cycles: Insights and Challenges. *Journal of Economic Literature*, 52 (4): 993–1074.

Beaudry, P., D. Nam, and J. Wang (2011). *Do Mood Swings Drive Business Cycles and Is It Rational?* Working Papers 17651. National Bureau of Economic Research.

Bolboaca, M. and S. Fischer (2017a). News as Slow Diffusing Technology. Mimeo.

— (2017b). Unraveling News: Reconciling Conflicting Evidences. Mimeo.

Bowker, R.R. (2017). *ISBN Output Report for 2002-2013*. URL: `http://media.bowker.com/documents/isbn_output_2002_2013.pdf` (visited on 10/24/2017).

Bradley, J., B. Fulton, M. Helm, and K. Pittner (2011). Non-traditional book publishing. *First Monday*, 16 (8).

Comin, D.A., M. Gertler, and A.M. Santacreu (2009). *Technology Innovation and Diffusion as Sources of Output and Asset Price Fluctuations*. Working Paper 15029. NBER.

Eden, M. and H. Nguyen (2016). Reconciling Micro- and Macro-Based Estimates of Technology Adoption Lags in a Model of Endogenous Technology Adoption. In: *Understanding the Income and Efficiency Gap in Latin America and the Caribbean*. Chap. 3, p. 57–72.

Farfan, B. (2017). *Is Barnes and Noble the World's Largest Bookstore?* URL: `https://www.thebalance.com/is-barnes-amp-noble-the-worlds-largest-bookstore-2892133` (visited on 10/25/2017).

Fernald, J. (2014). A Quarterly, Utilization-Adjusted Series on Total Factor Productivity. *Federal Reserve Bank of San Franciso*, (2012-19). Working Paper Series.

Galí, J. (1999). Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations? *The American Economic Review*, 89: 249–271.

Greco, A. N., J. Milliot, and R. M. Wharton (2014). The Book Publishing Industry, Third Edition. Routledge.

Holley, R. P. (2014). Self-Publishing: A New Challenge for Universal Bibliographic Control. In: 80th IFLA World Library, Information Congress General Conference, and Assembly, Lyon, France.

Kilian, L. and H. Lütkepohl (2017). Structural Vector Autoregressive Analysis. Cambridge University Press.

Kydland, F. E. and E. C. Prescott (1982). Time to Build and Aggregate Fluctuations. *Econometrica*, 50 (6): 1345–1370.

Liew, V. K.–S. (2004). Which Lag Length Selection Criteria Should We Employ? *Economics Bulletin*, 3 (33): 1–9.

Nord, D. P. and L.J. Miller (2009). A History of the Book in America: Volume 5: The Enduring Book: Print Culture in Postwar America. In: ed. by D. P. Nord, J. S. Rubin, and M. Schudson. University of North Carolina Press. Chap. Reading the data on books, newspapers, and magazines: A statistical appendix, p. 501–517.

Peters, J. (1992). Book industry statistics from the R. R. Bowker Company. *Publishing Research Quarterly*, 8 (3): 12–23.

Ramey, V.A. (2016). Handbook of Macroeconomics. In: ed. by J.B. Taylor and H. Uhlig. North-Holland. Chap. Macroeconomic Shocks and Their Propagation, p. 71–161.

Uhlig, H. (2004). Do Technology Shocks Lead to a Fall in Total Hours Worked? *Journal of the European Economic Association*, 2 (2-3): 361–371.

Appendices

A Data

The data I use in this paper is for the US economy. The Bowker book-based indicators are constructed using information from the Bowker annual reports on US print book production. The data is collected from the reports on US book titles (ISBN output) by category for the groups technology, science, and history. The dataset I construct for the sample period 1955-2012 contains data from three sources.[51] For the period 1955-1997, I use the dataset of Alexopoulos (2011), which is publicly available on the journal's website. For the period 1998-2001, I take the data from Greco et al. (2014). The data for the period 2002-2012 is obtained from Bowker's website (Bowker (2017)).

The MARC records-based indicator, TECH2, at annual frequency, is constructed by Alexopoulos (2011) for the period 1955-1997, and made publicly available on the journal's website.

The technological standardization-based indicators are created by Baron and Schmidt (2017) at quarterly frequency using the standards documents registered in the Searle Center database. The data is available for the period 1949Q1-2014Q4.[52] Using this data I construct also annual series, of which I use different subsamples depending on the timespan of the other annual series employed in the analysis.

I use the series of TFP adjusted for variations in factor utilization constructed with the method of Fernald (2014) based on Basu et al. (2013) and Basu et al. (2006).The series for the nonfarm business sector, annualized, and as percent change, is available on the homepage of the Federal Reverse Bank of San Francisco.[53]. The series is available both at quarterly and annual frequency. To obtain the log-level of TFP, I construct the cumulated sum of the original series, which is in log-differences.

Data for output, investment and consumption, both at quarterly and annual frequency, is from the Bureau of Economic Analysis. For output I use the real gross value added for the nonfarm business sector, while for consumption I use the sum of personal consumption expenditures for nondurable goods and personal consumption expenditures for services. Similarly, for investment I consider the sum of personal consumption expenditures on durable goods and gross private domestic investment.

I obtain data on hours worked, both at quarterly and annual frequency, from the Bureau of Labor Statistics. As a measure of hours worked, I use the hours of all persons in the nonfarm business sector.

[51] There is no single source that provides publicly the series for the whole period except for Bowker, but when contacted via email a company's representative refused to offer me this data claiming that they do not share this information for academic purposes anymore.

[52] Baron and Schmidt (2017) employ the subsample 1975Q1-2011Q4.

[53] `http://www.frbsf.org/economic-research/total-factor-productivity-tfp/`

Quarterly data on population and price level is also from the Bureau of Labor Statistics. Population defines all persons with ages between 15 and 64 from the US and the price level is the implicit price deflator for the nonfarm business sector. Annual data for the price level is from the Bureau of Economic Analysis and it is defined by the implicit price deflator for gross domestic product. Annual data for population is obtained from the Organization for Economic Co-operation and Development.

The index of consumer sentiment is from the University of Michigan. The University of Michigan conducts surveys of consumers and provides, among others, the index of consumer sentiment at monthly, quarterly, and annual frequency.[54]

Quarterly data is available for the sample period 1955Q1-2014Q4. Annual data for most variables covers also this sample period, with the exception of the index of consumer sentiment and hours worked, which are only available starting from 1961, and 1964, respectively. Moreover, for some of them, the latest available data point is for 2012 (or 2012Q4). Hence, I restrict the sample period to cover the timespan between 1964 and 2012.

B Bowker's Book-Based Indicators

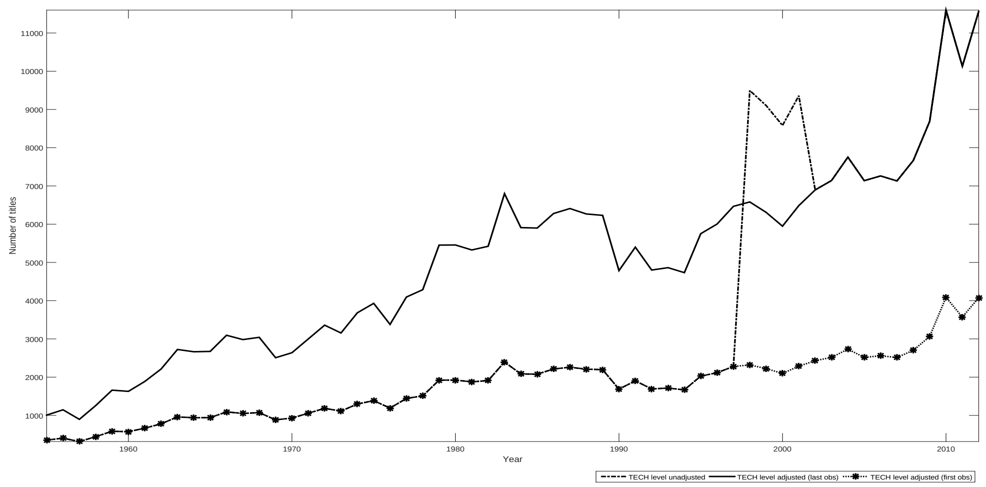

Figure 10: The annual series for the Bowker's book titles in the category technology (TECH) for the sample period 1955-2012. The dotted line corresponds to the original data with level breaks in 1998 and 2002. The solid line defines the break-adjusted level data obtained by fixing the level for the reference period to the latest available data point, while the starred line represents the break-adjusted level data obtained by fixing the level for the reference period to the first available data point.

[54]Details about the surveys and computation of measures are available on `https://data.sca.isr.umich.edu/`.

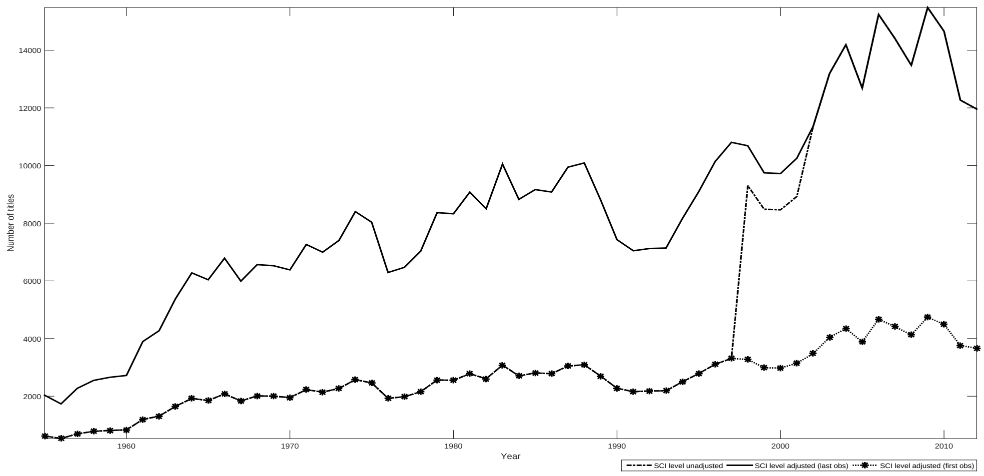

Figure 11: The annual series for the Bowker's book titles in the category science (SCI) for the sample period 1955-2012. The dotted line corresponds to the original data with level breaks in 1998 and 2002. The solid line defines the break-adjusted level data obtained by fixing the level for the reference period to the latest available data point, while the starred line represents the break-adjusted level data obtained by fixing the level for the reference period to the first available data point.

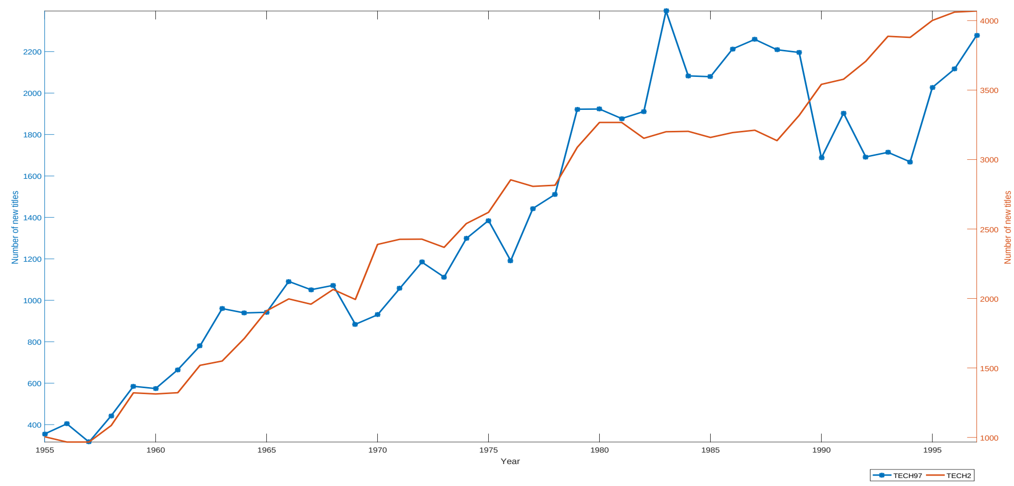

Figure 12: Comparison of the annual series for new titles in the category technology for the sample period 1955-1997, which are used in Alexopoulos (2011). The starred blue line corresponds to the indicator based on Bowker's book titles in the category technology (TECH97). The solid orange line defines the MARC records-based indicator for the field of technology (TECH2).

C Standards-Based Indicators

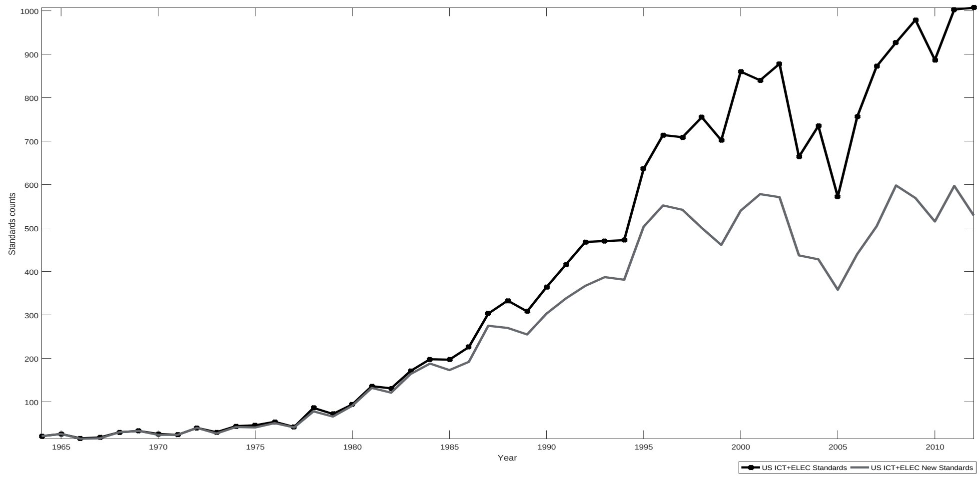

Figure 13: Comparison of the annual series for the counts of standards on ICT and electronics that were released in the US in the period 1964-2012. The black starred line corresponds to the total number of standards on ICT and electronics, while the gray solid line indicates the number only of new standards on ICT and electronics.

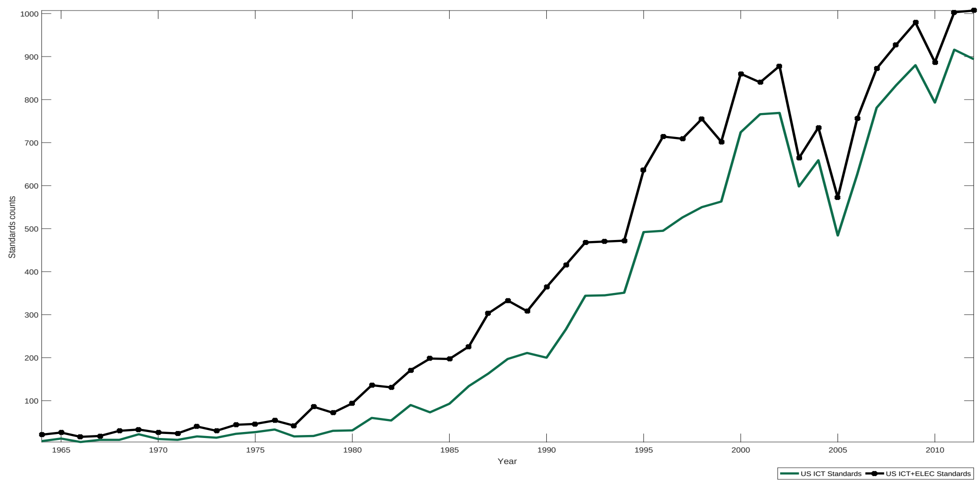

Figure 14: Comparison of the annual series for the counts of standards on ICT only and on ICT along with electronics that were released in the US in the period 1964-2012. The black starred line corresponds to the total number of standards on ICT and electronics, while the green solid line indicates the number of standards only on ICT.

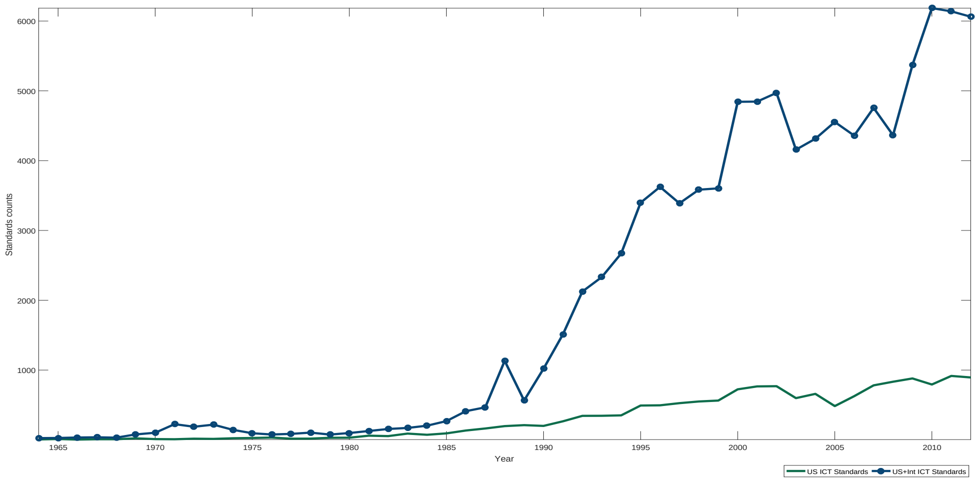

Figure 15: Comparison of the annual series for the counts of standards on ICT that were released in the US and those released in the US and internationally in the period 1964-2012. The blue dotted line corresponds to the total number of standards on ICT released by US and international SSOs, while the green solid line indicates the number of standards on ICT released in the US.

D Results Obtained Using Bowker's Book-Based Indicators

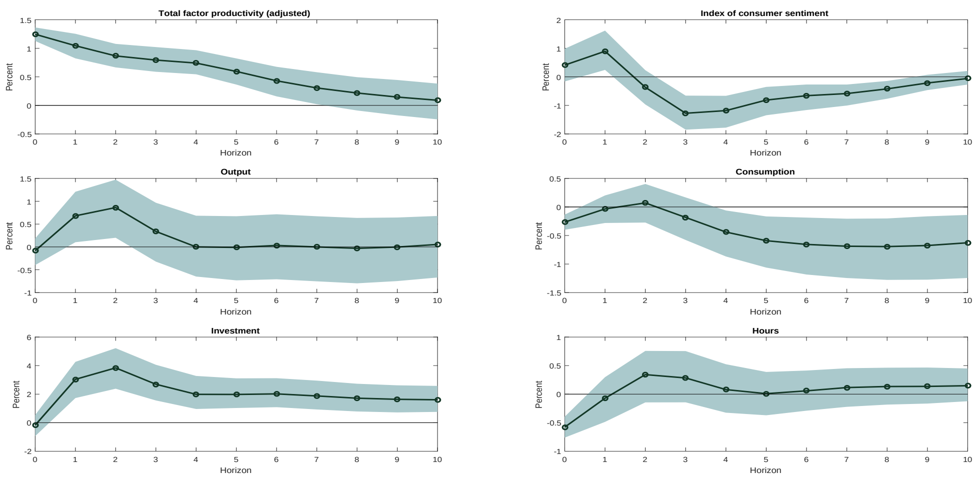

Figure 16: Impulse responses to the unanticipated productivity shock. The green circled line corresponds to the impulse responses to a one standard deviation unanticipated productivity shock. The shaded area corresponds to the 68% confidence intervals. The unit of the horizontal axis is years and of the vertical axis is percentage points.

The impulse responses in Figure 16 are obtained in four-variables VAR models, estimated with two lags. The first three were obtained in a model that contained TFP, TECH, index of consumer sentiment, and output. The last three were obtained in the same model by replacing output by one of the other three variables, consumption, investment, and hours worked, respectively. The unanticipated productivity shock is defined as the only shock with immediate effect on TFP. All the other variables of the model are allowed to respond instantaneous to the unanticipated productivity shock.

Figure 17 displays the bias corrected mean impulse responses to a one standard deviation positive technology shock (SCI). These results are obtained in the three-variables VAR model, estimated with two lags, but in which variable TECH was replaced by SCI. The impulse responses reported in Figure 18 are obtained after estimating four-variables VAR models in which each of the variables is included as the forth. The first three variables are TFP, TECH or SCI (depending on the model), and the index of consumer sentiment. The forth variable is output, consumption, investment, or hours worked. The models are estimated with two lags. The impulse responses reported in Figure 19 and Figure 20 are obtained after estimating three-variables VAR models. The three variables are TFP, TECH97 or TECH2 (depending on the model), and the index of consumer sentiment, output, consumption, investment, or hours worked, as the third. The models are estimated with two lags. The sample period is 1964-1997.

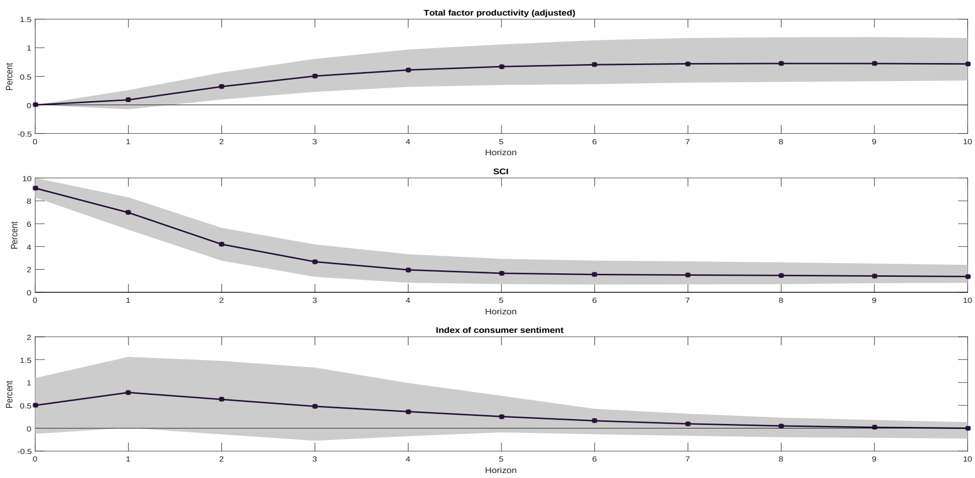

Figure 17: Impulse responses to a one standard deviation positive technology shock (SCI). The shaded area corresponds to the 68% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR. The horizontal axis indicates the forecast horizon (years) and the unit of the vertical axis is percentage points.

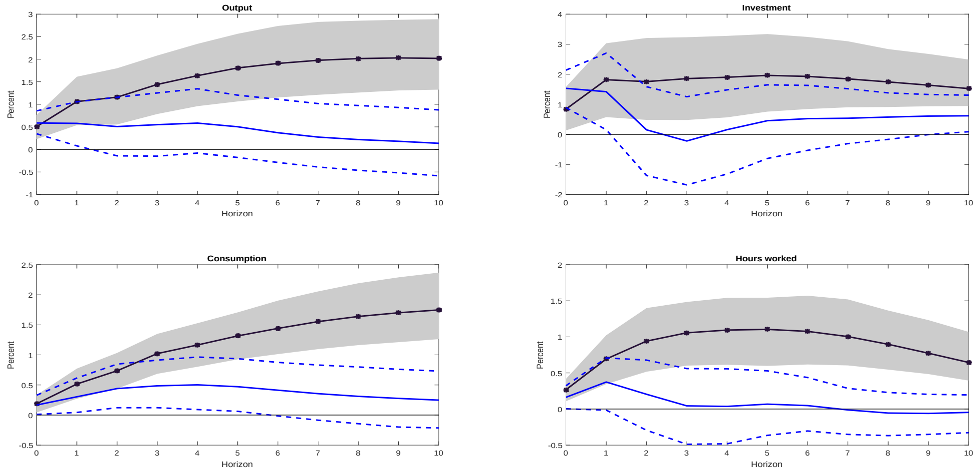

Figure 18: Comparison of technology shocks. The black starred line corresponds to the impulse responses to a technology shock, on variable TECH and the shaded area defines the 68% confidence interval. The blue solid line corresponds to the impulse responses to a technology shock, on variable SCI, while the dotted blue lines delimit the 68% confidence interval. The unit of the horizontal axis is years and of the vertical axis is percentage points.

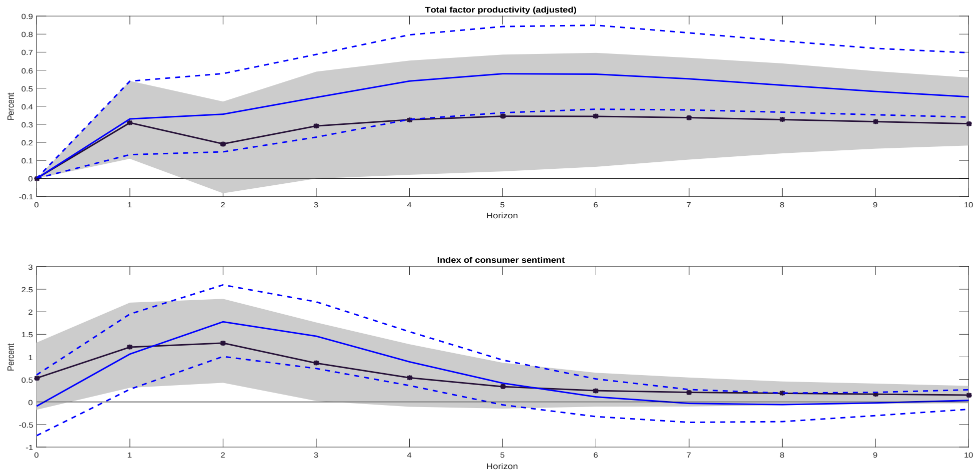

Figure 19: Comparison of technology shocks. The black starred line corresponds to the impulse responses to a technology shock, on variable TECH97 and the shaded area defines the 68% confidence interval. The blue solid line corresponds to the impulse responses to a technology shock, on variable TECH2, while the dotted blue lines delimit the 68% confidence interval. The unit of the horizontal axis is years and of the vertical axis is percentage points.

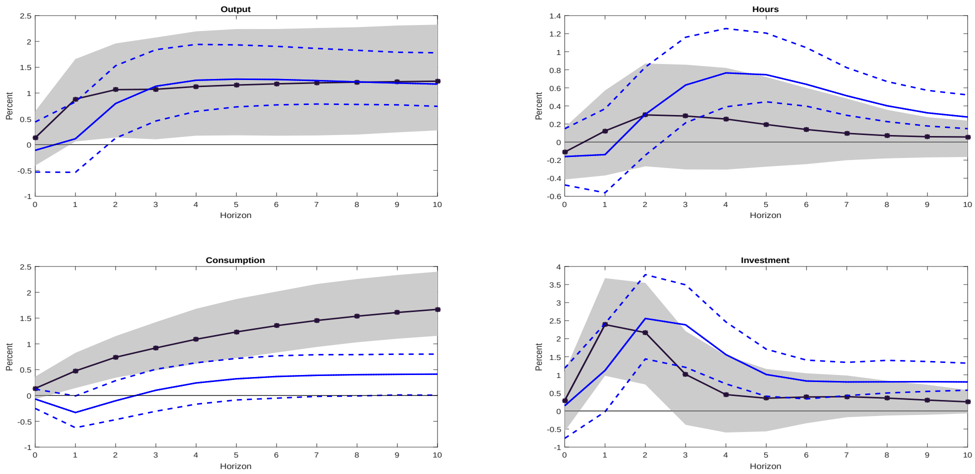

Figure 20: Comparison of technology shocks. The black starred line corresponds to the impulse responses to a technology shock, on variable TECH97 and the shaded area defines the 68% confidence interval. The blue solid line corresponds to the impulse responses to a technology shock, on variable TECH2, while the dotted blue lines delimit the 68% confidence interval. The unit of the horizontal axis is years and of the vertical axis is percentage points.

E Results Obtained Using Standards-Based Indicators

Table 6: Forecast Error Variance Decomposition of TFP and ICS. The numbers indicate the percent of the FEV of TFP and ICS explained by the unanticipated productivity, technology and news shocks at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
Unanticipated productivity shock	98.93	78.26	72.41	47.70	36.65
Technology shock	0.50	2.41	5.49	34.12	48.57
News shock	0.08	17.42	19.37	14.44	10.99
Index of consumer sentiment					
Unanticipated productivity shock	11.05	26.75	27.74	27.75	27.82
Technology shock	1.99	17.04	18.89	20.09	20.12
News shock	85.85	53.85	50.79	48.86	48.75

The shares displayed in Table 6 and Table 7 are the average of the contributions obtained in the three-variables VAR model (TFP, US ICT+ELEC Standards, index of consumer sentiment) and in the four-variables VAR models with output, consumption, investment, or hours worked as the forth variable. The shares obtained in each of these models can be provided by the author.

Table 7: Forecast Error Variance Decomposition of macro variables. The numbers indicate the percent of the FEV of output, consumption, investment, and hours worked explained by the technology shock on variable US ICT+ELEC Standard and the news shock, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Output					
Technology shock	1.49	25.4	36.71	65.65	73.89
News shock	56.08	48.08	40.63	21.64	16.37
Consumption					
Technology shock	2.58	48.08	62.45	87.69	91.32
News shock	42.63	36.25	18.27	5.78	3.63
Investment					
Technology shock	2.48	15.01	18.96	27.87	31.46
News shock	54.02	46.48	43.24	36.29	33.85
Hours worked					
Technology shock	8.3	18.97	35.76	37.16	37.39
News shock	46.17	31.83	28.36	27.43	27.22

The impulse responses for TFP, and the index of consumer sentiment, reported in Figure 21, are obtained after estimating a three-variables VAR model, which contains TFP, the indicator of technological change (US ICT+ELEC Standards, US ICT+ELEC New Standards, US ICT Standards, or US+Int ICT Standards), and the index of consumer sentiment. The other impulse responses are obtained after estimating a four-variables VAR models with output, consumption, investment, or hours worked, added as the forth. The models are estimated with two lags. The sample period is 1964-2012.

The results reported in Figures 22 - 25 are obtained after estimating a seven-variables VAR model, which contains TFP adjusted for capacity utilization, the indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards), the index of consumer sentiment, investment, hours worked, output, and consumption. The model is estimated with four lags using quarterly data covering the period 1964Q1-2012Q4.

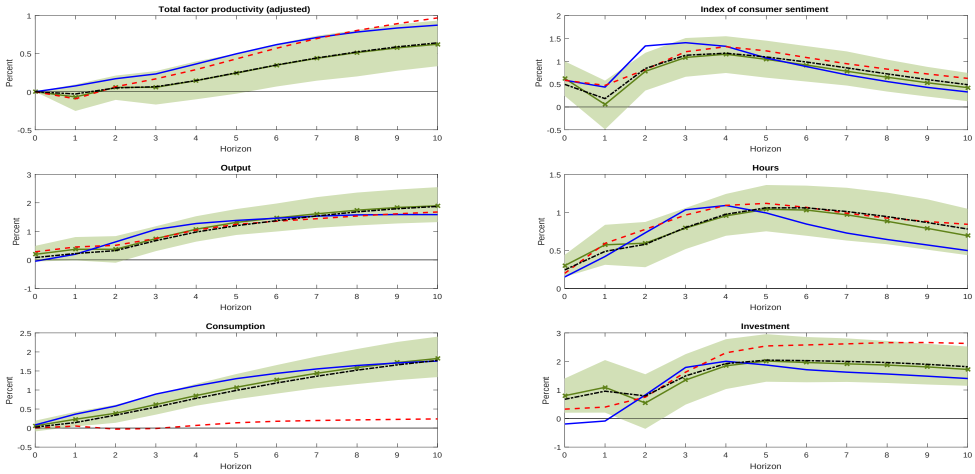

Figure 21: Comparison of technology shocks. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the shaded area is the corresponding 68% confidence interval. The black dotted line defines the impulse responses to a technology shock on variable US ICT+ELEC New Standards. The blue line gives the impulse responses to a technology shock on variable US ICT Standards and the red dotted line is for the technology shock on variable US+Int ICT Standards. The unit of the horizontal axis is years and of the vertical axis is percentage points.

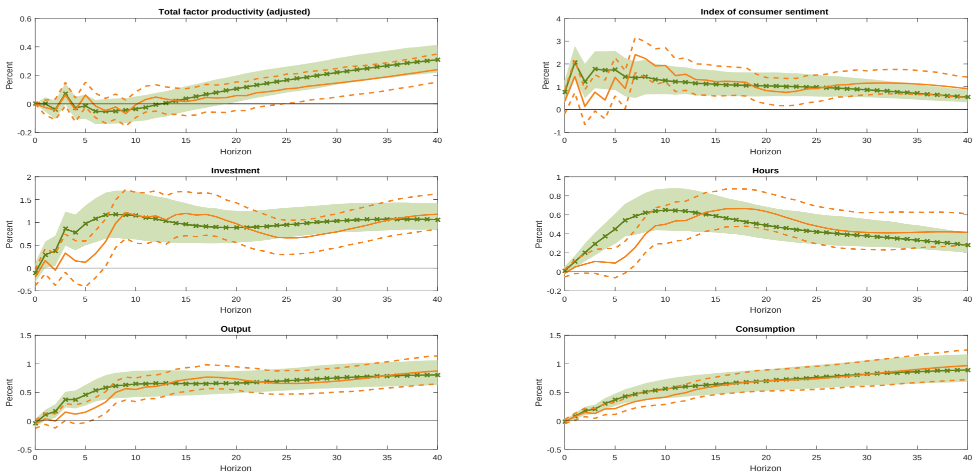

Figure 22: Comparison of technology shocks obtained in models estimated with different lag lengths. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards obtained in a model estimated with four lags and the shaded area is the corresponding 68% confidence interval. The orange solid line represents the impulse responses to the same technology shock obtained in a model estimated with eight lags and the dotted orange lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters and of the vertical axis is percentage points.

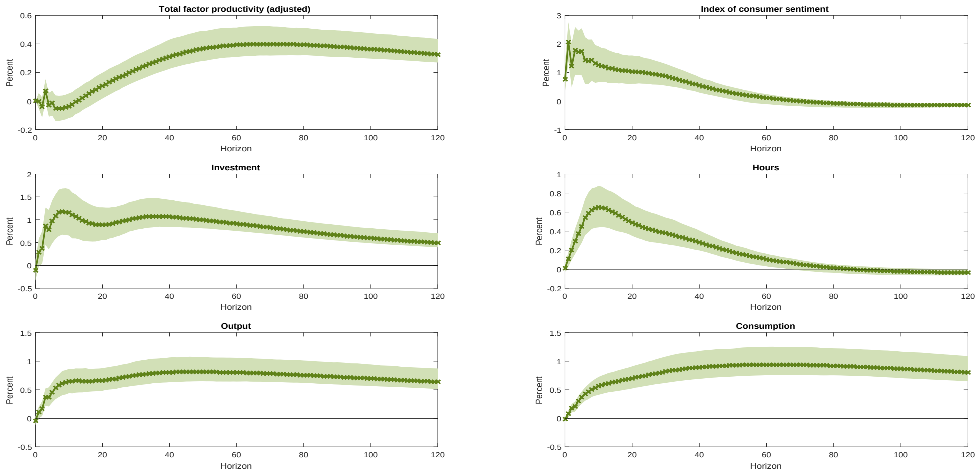

Figure 23: Impulse responses to the technology shock. The green crossed line represents the impulse responses to the technology shock on variable US ICT+ELEC Standards, obtained in the model estimated with four lags. The shaded area is the corresponding 68% confidence interval.The unit of the horizontal axis is quarters and of the vertical axis is percentage points.

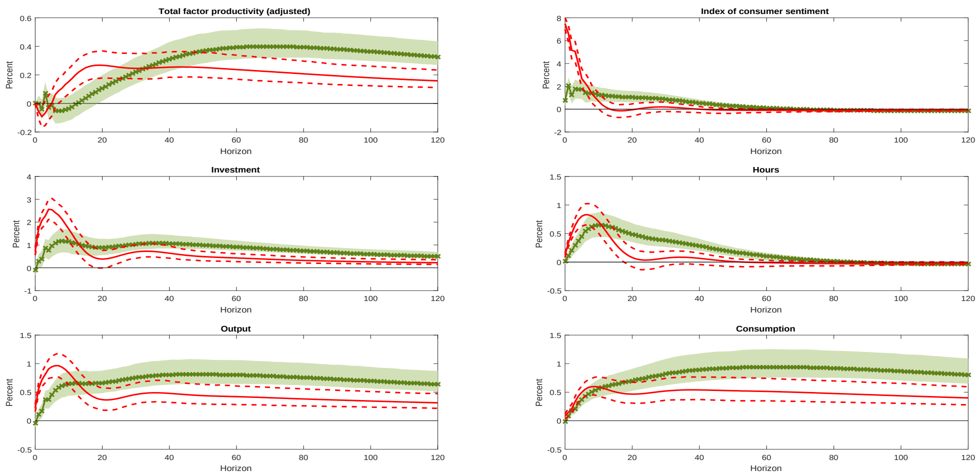

Figure 24: Comparison between the technology shock and the news shock. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards and the shaded area is the corresponding 68% confidence interval. The red solid line represents the impulse responses to a news shock and the dotted red lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters and of the vertical axis is percentage points.

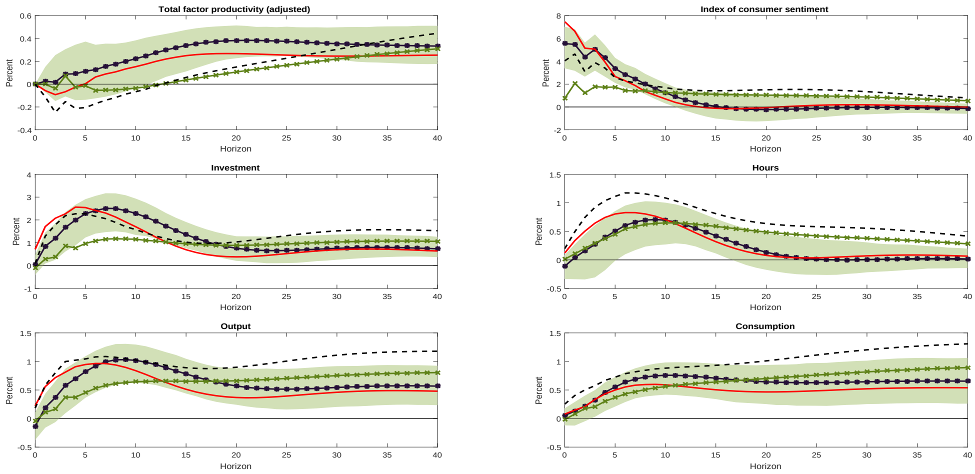

Figure 25: Comparison between the technology shock and the news shocks. The dark blue circled line defines the news shock obtained using medium-run restrictions, with a truncation horizon of 10 years. The shaded area is the corresponding 68% confidence interval. The black dotted line defines the news shock obtained using medium-run restrictions, with a truncation horizon of 20 years. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards and the red solid line represents the impulse responses to a news shock, obtained with short-run restrictions. The unit of the horizontal axis is quarters and of the vertical axis is percentage points.