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Technological Standardization, Endogenous Productivity and Transitory Dynamics

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Abstract

We uncover technological standardization as a microeconomic mechanism which is vital for the implementation of new technologies, in particular general purpose technologies. The interdependencies of these technologies require common rules ("standardization") to ensure compatibility. Using data on standardization, we are therefore able to identify technology shocks and analyze their impact on macroeconomic variables. *First*, our results show that technology shocks diffuse slowly and generate a positive S-shaped reaction of output and investment. Before picking up permanently, total factor productivity temporarily decreases, suggesting that the newly adopted technology is incompatible with installed physical, human and organizational capital. *Second*, standardization can reveal news about future movements of macroeconomic aggregates as evidenced by the positive and immediate reaction of stock market variables to the identified technology shock.

JEL-Classification: E32, O31, O33
Keywords: technology adoption, business cycle dynamics, standards, aggregate productivity, Bayesian vector autoregressions

Résumé

Cet article montre que la normalisation technologique est un mécanisme micro-économique décisif du processus d'appropriation et de mise en œuvre des nouvelles technologies, en particulier des technologies d'application générale. Les interdépendances entre ces technologies exigent des règles communes ("normalisation") pour assurer leur compatibilité. Les données sur la normalisation nous permettent d'identifier des chocs technologiques et d'analyser leur impact sur un certain nombre de variables macroéconomiques. *Tout d'abord*, nos résultats montrent que les chocs technologiques se diffusent lentement et qu'ils génèrent une réaction positive de la production et de l'investissement qui est caractéristique d'une courbe logistique. La productivité totale des facteurs décroît temporairement avant de croître de nouveau de manière permanente. Dans notre interprétation, ceci traduit le fait que les technologies nouvellement adoptées sont incompatibles avec le capital physique, humain et organisationnel en place. *Ensuite*, nos résultats indiquent que la normalisation peut révéler des informations sur le développement futur des agrégats macroéconomiques comme le montre la réaction positive et immédiate des variables liées aux marchés financiers en réponse au choc technologique identifié.

Classification JEL : E32, O31, O33
Mots clés : adoption des technologies, dynamiques des cycles conjoncturels, normes, productivité globale, modèles vectoriels autorégressifs bayésiens

Non-technical summary

This paper analyzes empirically the impact of technology on macroeconomic variables to gain more insight into the feedback mechanism between innovation and the cycle. To that end, we propose a new micro-founded indicator of technological change to study the role of technology shocks for macroeconomic fluctuations. We use the fact that technological standardization represents a prerequisite for the implementation of new technologies: The complex interdependencies of various technologies necessitate the coordinated establishment of rules. This process is called technological standardization.

Technology standards - similar to patents - are documents which describe detailed features of a technology. Prominent examples of standards are Internet protocols or mobile phone technologies such as the 1G, 2G, 3G and 4G standard families. In contrast to patents, standards are economically and technologically highly meaningful and reflect the actual adoption (instead of invention) of a new technology. Standardization is a particularly important step in the adoption of information and communications technologies (ICT) due to its key role in harmonizing technological devices and ensuring compatibility. Moreover, ICT has been shown to be a general purpose technology and has constituted *the* dominant technology in recent decades. We therefore concentrate our analyses on ICT standards. Technology shocks are usually composed of a large number of underlying drivers. In this paper, we identify a *specific* technology shock. Incremental technological progress, organizational restructuring or managerial innovation are not the focus of our analysis.

To construct our novel indicator of technology adoption, we count the number of ICT standard releases per quarter over the time period of 1975Q1–2011Q4. Using a dynamic empirical model (Bayesian vector autoregressions), we are able to identify technology shocks from standardization data. We estimate the reaction of macroeconomic variables, in particular output, investment and total factor productivity, to technology shocks and assess their quantitative contributions.

Our findings can be grouped into two major points. *First*, we find that standardization is an important driver for output and investment as well as for long-run productivity. The technology shock that we identify is very specific, but can nevertheless account for a considerable amount of fluctuations of macroeconomic variables. The contribution of our identified technology shock is more important for the long-run than for business-cycle frequencies. The transitory dynamics we are able to uncover contrast with previous findings. The reaction of output and investment to our technology shock is S-shaped. In particular, we find that total factor productivity decreases following a shock to embodied technology. The positive effect on productivity only materializes after years. We interpret this finding as an indication of the incompatibility of new and old vintages of capital. *Second*, we find that our identified technology shocks communicate information to economic agents about future productivity. Standardization triggers the adoption of technologies; although this implementation process is characterized by lengthy, S-shaped diffusion patterns, forward-looking variables like stock market indices pick up this information on impact. Our results therefore also help to gain insights about the nature of shocks such as the ones found in the "news shock" literature.

1 Introduction

Technology is a popular explanation for business cycle fluctuations. In this literature, however, the concept of technology is still vague and differs from the more literal interpretation of technology outside of macroeconomics. Business cycle economists – in contrast to endogenous growth theorists – have made little use of the findings from the industrial organization literature on innovation and technology adoption. Yet, a thorough understanding of the role of technology is necessary given that a large strand of the business cycle literature relies heavily upon technology shocks as a driver of short-run fluctuations.

This paper analyzes empirically the impact of technology on macroeconomic variables to gain more insight into the feedback mechanism between innovation and the cycle. To that end, we propose a new micro-founded indicator of technological change, namely technological standardization.[1] We argue that standardization precedes the implementation of new technologies and signals the arrival of technological change. Using a direct micro-level indicator of technological progress allows us to open the black box that technology generally constitutes in many business cycle studies.

Technology standards - similar to patents - are documents which describe detailed features of a technology. Prominent examples of standards are Internet protocols or mobile phone technologies such as the 1G, 2G, 3G and 4G standard families. In contrast to patents, standards are economically and technologically highly meaningful and reflect the actual adoption (instead of invention) of a new technology. Standardization is a particularly important step in the adoption of information and communications technologies (ICT) due to its key role in harmonizing technological devices and ensuring compatibility. Moreover, ICT has been shown to be a general purpose technology (Basu and Fernald, 2008) and has constituted *the* dominant technology in recent decades. We therefore concentrate our analyses on ICT standards. Technology shocks are usually composed of a large number of underlying drivers. In this paper, we identify a *specific* technology shock. Incremental technological progress, organizational restructuring or managerial innovation are not the focus of our analysis. We isolate a technology shock which can be interpreted as fundamental technological change and is very likely to affect the economy on the aggregate. This allows us to uncover general mechanisms that are characteristic of technological diffusion.

"Technology" can comprise a variety of concepts. In the context of this paper, we refer to technological change as affecting *new* vintages of capital. It thus requires investment in new machinery and human capital to realize technological progress. In particular, the concept of "vintage capital" stresses that technological change leads to technological obsolescence and economic depreciation (as opposed to physical depreciation).[2] This notion

[1] To our knowledge, there is only one other paper that treats the concept of "standardization" in a macroeconomic setting. In Acemoglu *et al.* (2012), however, standardization is concerned with the introduction of more routine ("standardized") production processes. Therefore, the authors model standardization as the process of turning an existing high-tech product into a low-tech one. This allows manufacturers to produce at lower cost as skilled workers can be replaced by unskilled ones. In contrast, the concept of "standardization" in this paper specifically refers to *technology standards* and the activity of standard-setting organizations (SSOs). Here, standardization ensures the compatibility of one or several potentially *complex* technologies *across firms*, whereas the term "standardization" as used by Acemoglu *et al.* (2012) concerns the internal organization of production processes within a given firm.

[2] See Cooley *et al.* (1997) for a discussion on the concept of economic depreciation.

of technology is closely related to the one used in the literature on shocks to the efficiency of new investment goods as defined by Greenwood *et al.* (1988). These investment-specific technology (IST) shocks have been shown to play an important role for macroeconomic dynamics.[3]

The recent literature on "news shocks" (Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009; Schmitt-Grohé and Uribe, 2012) has also contributed to the revival of the idea that technology, or more precisely news about future technological improvements, drive business cycles. Anticipated improvements in total factor productivity lead to business cycle fluctuations despite the fact that the shock only materializes after several lags. The "news shock" literature relates to the present paper because standardization acts as a signalling mechanism about future technological change. As diffusion lags are long, the responses of macroeconomic variables resemble the ones triggered by news shocks.

We attempt to account for technology as an economic phenomenon instead of considering technology as a simple exogenous force. To this end, we make use of concepts that are well established in innovation economics and the growth literature. *First*, technology is endogenous to the cycle which is why we use a vector autoregression (VAR) approach to model such complex interactions. In our empirical analysis, we do indeed find that standardization is partly cycle-driven. *Second*, we specifically adapt our VAR model to the context of slow technology diffusion by opting for a generous and variable-specific lag length to capture the importance of distant technology lags for the dynamics of the system. We introduce this feature into macroeconometric modelling by using Bayesian techniques.

Our findings can be grouped into two major points. *First*, we find that standardization is an important driver for output and investment as well as for long-run productivity. The technology shock that we identify is very specific, but can nevertheless account for up to 6% of business cycle fluctuations and 19% of fluctuations at lower frequencies. The transitory dynamics we are able to uncover contrast with previous findings. The reaction of output and investment to our technology shock is S-shaped. In particular, we find that total factor productivity (TFP) decreases following a shock to embodied technology. The positive effect on productivity only materializes after years. We interpret this finding as an indication of the incompatibility of new and old vintages of capital. *Second*, we find that our identified technology shocks communicate information to economic agents about future productivity in the spirit of Beaudry and Portier (2006). Standardization triggers the adoption of technologies; although the implementation process is characterized by lengthy, S-shaped diffusion patterns, forward-looking variables like stock market indices pick up this information on impact.

The next section motivates and discusses the relevance of our new measure of technological change. Section 3 and 4 describe the data and the econometric methodology. Section 5 discusses the results while section 6 investigates the robustness of the findings. Finally, Section 7 concludes.

[3]IST shocks can be either thought of as lowering the cost of investment (and thus increasing the quantity of new investment goods) or improving the productivity, and thus quality, of new investment. Greenwood *et al.* (1997, 2000) show that more than 60% of long-term productivity growth and 30% of short-term fluctuations are driven by investment-specific technological change. Justiniano *et al.* (2010) find IST shocks to account for about 50% of business cycle volatility. Fisher (2006) analyzes the effects of neutral and investment-specific technology shocks and finds that the latter is the larger driver of volatility.

2 Standardization and technology adoption

Most of the empirical research on the effects of technology shocks on business cycles uses identification schemes which deduce technology shocks from macroeconomic data (King *et al.*, 1991; Galí, 1999; Basu *et al.*, 2006). As an alternative approach, one can employ direct measures of technological change. One the one hand, a vast literature relies on R&D and patent data to capture direct indicators of *inventive* activity (Shea, 1999; Kogan *et al.*, 2012). However, R&D expenditures and patent counts often tell little about the economic significance of an innovation and are only loosely related to the actual implementation of new technologies. Therefore, on the other hand, proxies for the *adoption* of technological innovations have been used. One important contribution in this literature is Alexopoulos (2011) who relies on technology publications, i.e. manuals and user guides, as a measure for technology adoption.

Technological progress exists in many diverse and unrelated technological fields. However, if embodied technology shocks are to have an effect on the aggregate business cycle, then they are most likely to stem from the implementation of general purpose technologies (GPTs). These technologies affect the production processes of a large number of sectors and thus generate aggregate long-term growth (see for example Helpman and Trajtenberg, 1996). Examples of GPTs are the steam engine, railroads or electricity. Over the past decades, the dominant general purpose technologies were Information and Communication Technologies (ICT), affecting production and the way of doing business in all sectors of the economy (Basu and Fernald, 2008).

The adoption of new GPTs, and in particular ICT, is characterized by *compatibility requirements*: different technological applications have to be based on common features in order to benefit from the positive externalities which interdependent technologies generate (Katz and Shapiro, 1985). In order to achieve compatibility, industry-wide efforts are made to implement a minimal set of rules for all producers and users of the technology. This process is called standardization and is a vital step in the adoption of new technologies. In this paper, we exploit the standardization process that is at the heart of the adoption of ICT technologies for the identification of economy-wide technology shocks.[4]

2.1 The standard-setting process

Technology standards play an important role in industrialized societies. Prominent examples of standards include electricity plugs, paper size formats or quality standards (e.g. ISO 9001:2008). A standard describes required technological features of products and processes. The purpose of standardization can be to ensure reliability, safety or quality. Most ICT standards are compatibility standards, i.e. their function is to ensure that a technical device is compatible with complementary devices and inter-operable with competing products.

There are several ways to achieve standardization, notably through formal standardization (voluntary and regulatory standards) as well as de facto standardization. Many

[4]We therefore use 'standardization', i.e. the decision by members (firms) of an SSO's working group to adopt a new technology, and 'technology adoption' interchangeably.

voluntary standards are set by standard setting organizations (SSOs). Examples are the Internet Engineering Task Force (IETF) or the European Telecommunications Standards Institute (ETSI). Some SSOs are established organizations, but they can also be informal interest groups. Regulatory standards are binding regulations set by national or international SSOs, developed upon request or approved a posteriori by governmental authorities.[5] While there are hundreds of standard setting organizations and consortia, a few large organizations dominate the standard setting process. According to the American National Standards Institute (ANSI), the 20 largest SSOs produce about 90% of all standards.[6] Not all standards are set by SSOs. As such, de facto standards are set by a market selection process where adoption choices gradually converge. An example of a de facto standard is the QWERTY keyboard.

Table 1: Characteristics by ICS classification 1975Q1–2011Q4

	Number		% new	
	US	US+Int	US	US+Int
Health/safety/environment/agriculture/food	10 140	20 032	47	51
ICT	9 603	62 753	68	56
Engineering/electronics	27 772	49 064	45	51
Materials technologies	30 801	41 004	32	37
Transport/construction	30 782	40 108	46	47
Generalities/infrastructures/sciences/etc.	7 432	16 327	40	51
Total	107 480	209 988	44	49

Notes: The table summarizes information on the data series over the time period 1975Q1–2011Q4. "US" refers to standards released by US standard setting organizations whereas "US+Int" refers to standards released both by US and international standard setting organizations. "% new" refers to the percentage of standards in the sample which are new, i.e. which are not upgrades of already existing standards.

In this paper, we use standards issued by SSOs to measure the intensity of technology adoption at a given point in time. In particular, we construct time series by counting the number of standards released per quarter. The International Classification of Standards (ICS) system allows us to assign each standard to a specific technological field. In addition, we are able to differentiate across different SSOs and construct series for standards released by US SSOs ("US") as well as those released by both US and international SSOs which also apply to the US ("US+Int"). Table 1 shows that the database we are extracting for the period 1975Q1–2011Q4 contains a total of over 200 000 standards of which roughly 30% are ICT standards. Other technological fields in which a large amount of standards are released are engineering and electronics as well as materials, transport and construction technologies.

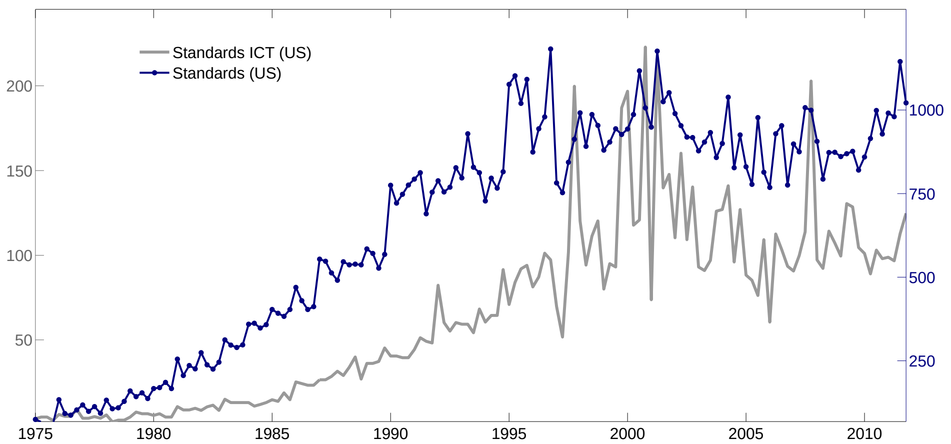
For the main analysis in this paper, we will use standards released by US SSOs as these are the most relevant for the US economy. In addition, some of the most important standards released by international SSOs are often simultaneously accredited by US SSOs and will thus be included in our data series. In the robustness section of this paper, we

[5]Examples of standard setting organizations issuing regulatory standards are the American National Standards Institute (ANSI) or the International Organization for Standardization (ISO). These organizations however also issue voluntary industry standards.

[6]See the Domestic Programs Overview on ANSI's website:
http://www.ansi.org/standards_activities/domestic_programs/overview.aspx?menuid=3

will further discuss the data series obtained using standards from international SSOs and will show that the results hold. Figure 1 plots the standard count for ICT standards released by US SSOs and compares them to the total number of standards. We can observe a continuous increase in the 1980s and 1990s, but also note a substantial amount of variability in the data.

Figure 1: Standard series 1975Q1–2011Q4



Notes: The series display the number of standard counts per quarter. The left-hand side y-axis corresponds to ICT standards and the right-hand side corresponds to the total number of standards across all ICS classes which were released by US standard setting organizations over the period 1975Q1–2011Q4.

2.2 Economic implications of standardization

Standardization is associated with important benefits (Farrell and Saloner, 1985). *First*, compatibility across different products, technologies and their sub-components increase the positive externalities associated with the growing number of users of a particular product (Katz and Shapiro, 1985). Compatibility requirements can even be indispensable for the introduction of new products. *Second*, market transactions can be facilitated due the use of a common definition of the underlying product. *Third*, economies of scale and scope can arise when the manufacturing of different products uses complementary intermediate goods. A similar argument is made by Acemoglu *et al.* (2012) who define standardization as a simplification of manufacturing processes which allows for lower production costs as skilled labour can be replaced by unskilled labour.[7]

All of the above points are relevant for assessing the benefits of standardization, but it is above all compatibility requirements that constitute a prerequisite for the implementation of (ICT) technologies and therefore allow us to identify technology shocks. More than

[7]One should note that the definition of standardization in Acemoglu *et al.* (2012) is somewhat different from ours. Whereas Acemoglu *et al.* (2012) refer to the facilitation of production processes by adapting products to be manufactured by unskilled workers, we define standardization as the explicit agreement and documentation of requirements and specifications of products' underlying components and therefore refer to the quintessential field of activity of SSOs. Therefore, in Acemoglu *et al.* (2012) concentrate on the cost-saving effects of the simplification of production processes within a firm whereas this paper is concerned with the positive externalities associated with industry-wide compatibility resulting from standardization.

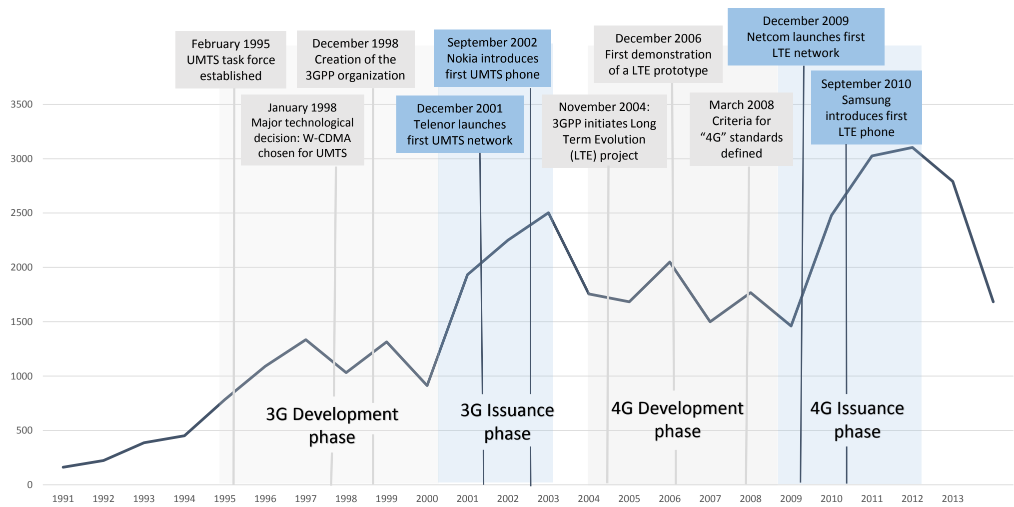
merely finding a new indicator of technology adoption, we are interested in uncovering an economic channel through which the supply of new technologies translates into the actual adoption of these technologies.

Selection mechanism. Many potentially useful inventions coexist without (yet) being marketed. Rysman and Simcoe (2008) show that SSOs are used by firms to determine which technologies are the most relevant. In the process of standard setting, firms negotiate an agreement on a large set of inter-related technological choices. The necessity to standardize interdependent technologies introduces an explicit selection mechanism where one technology is chosen among competing ones for common use by an entire industry.

Occasionally, an already commercialized technology can be standardized *ex post*. In this case, standardization creates positive externalities by facilitating its use in a wider range of industries and markets. However, when interdependencies among technologies are very strong, mass production requires the explicit standardization *before* the market introduction of a technology. This is especially the case in ICT.

Clustered adoption and implementation of new technologies. While inventions are contingent upon unpredictable research outcomes, the coordinated decision to adopt a technology constitutes an intentional *economic* decision. Due to technological interdependencies, many standards are adopted at the same time. Adoption is clustered as a large number of single inventions are bundled into complex technological systems. Figure 1, which plots the time series count of different standard series, illustrates this point: the time series are very erratic, thus implying that standardization is a very "lumpy" process. Standardization therefore represent a channel of technology adoption which discretizes an otherwise smooth technology supply.

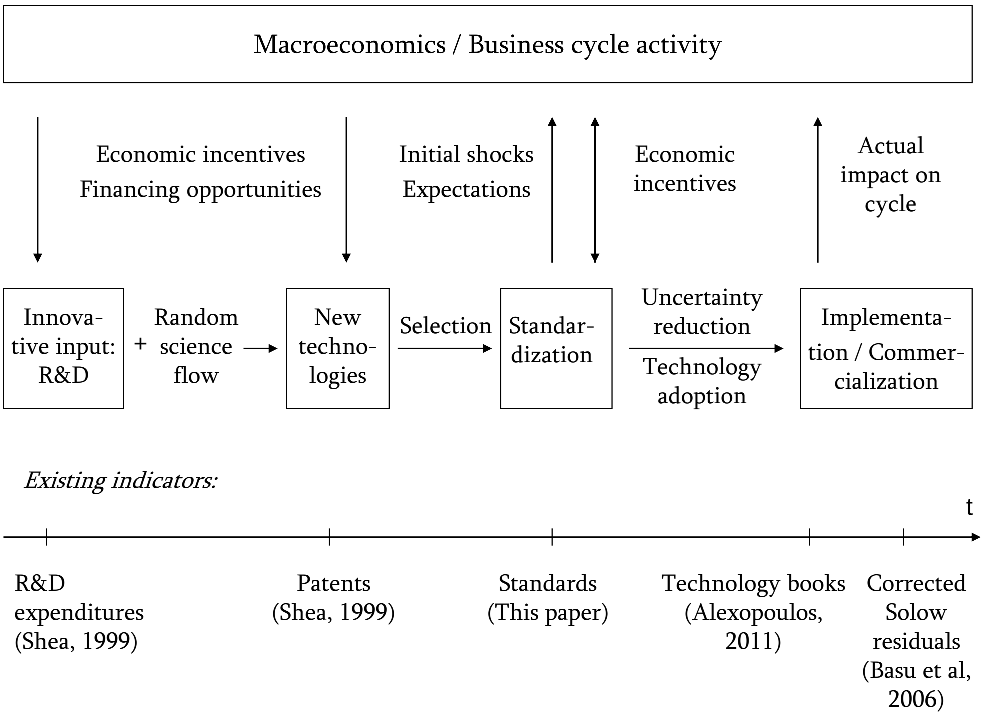
Figure 2: 3G and 4G development and issuance phases



Notes: The time series displays the number of standards released by the SSO 3GPP. Dark blue backgrounds and boxes correspond to the issuance phases of 3G (UMTS) and 4G (LTE) technology respectively. Data from Hillebrand *et al.* (2013).

One of the most important examples of technology adoption through standardization is mobile phone technology. The development phases of mobile phone technology are generally referred to as first, second, third and forth generation (1G, 2G, 3G and 4G). Figure 2 illustrates that the count of standard documents is an indicator of the bundled adoption of complex technological systems such as the 3G (UMTS) and 4G (LTE) technology standards developed at the SSO ETSI.[8] The development of a standard generation occurs over approximately ten years. During the development phase, a large number of incremental technological choices are made at the SSO, and many different companies invent and often patent thousands of technological solutions for different aspects of the future standard. For example, the 3G standard family UMTS comprises over 1200 declared essential patents held by 72 firms (Bekkers and West, 2009). The issuance of the new standard generations eventually occurs over a relatively short period. The issuance of each new generation irreversibly defines fundamental technological characteristics of the new technology, which is a prerequisite to the first deployment of telecommunication networks implementing the new standard and the first mass market sales of new generation mobile phones. The first steps towards market introduction of 3G and 4G respectively coincided with a peak in the number of standard documents released at 3GPP as shown in figure 2.

Figure 3: The interaction between the business cycle and technology



Signalling effects Along the development and adoption path of a technology, several indicators can be identified (see figure 3); however, as these indicators represent different stages of a very lengthy process, their economic meaning is different and so is their interaction with the business cycle. Figure 3, which displays a very schematic representation of the interaction between technology and the business cycle, shows that standardization is associated with the point in time when technology adoption is first signalled to the

[8] Long Term Evolution (LTE) is one among several 4G standard families that competed to succeed the 3G standard family Universal Mobile Telecommunication System (UMTS). ETSI, the European Telecommunications Standards Institute, is part of the 3rd Generation Partnership Project (3GPP), an alliance of six mobile telecommunications technology SSOs, since December 1998.

macroeconomic cycle. The issuance of standard documents releases information about the selection of a technology. Therefore, uncertainty is reduced as technological variety is narrowed down to a single standardized technology (Fontana *et al.*, 2009) and complementary investment into the new technology picks up. In this paper, we will interpret the nature of standards as signalling mechanisms in the light of the literature on the role of news for macroeconomic fluctuations (Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009).[9]

3 Description of the data

3.1 Data series and their respective sources

We employ data for the US economy. In order to retrieve time series on standardization, we use the PERINORM database and collect information on standards issued by formal standard setting organizations.[10] However, our data do not cover de facto standards or the standards issued by informal consortia or ad hoc industry groups. We are therefore only able to capture a part of the overall standardization process. However, it is common that informal standards are adopted only by a minority of industry participants and compete in the product market with other informal standards. When an informal standard emerges as the dominant technology from this competition, it is often accredited as a standard by one of the established formal SSOs in our sample. These organizations typically require a large industry consensus.[11] We are therefore confident that our measure of formal standards is representative.

Time series are constructed by counting the number of standards which are released per quarter. The PERINORM database allows to distinguish between SSOs of different nationality as well as international SSOs. In particular, we construct a standard time series that comprises formal industry standards issued by American standardization bodies, such as ANSI. We will work with the standard series from US SSOs in the main part of this paper and discuss the results obtained by adding standards from international SSOs in section 6. In this robustness section, we will also use certain standard characteristics (new vs. upgraded standards or the number of references) to assess the relevance of different standard documents. For a share of our standard counts, we only have information about the year, but not the month, of the release of the standard. We therefore adjust our final series by uniformly distributing the standards for which only the release year is known across the quarters in the respective year. This adjustment does not affect our results.[12] In section 6.4, we will present robustness checks using annual data to show that results hold

[9] As noted by Gandal *et al.* (2004) and Rysman and Simcoe (2008), standardization is an effective means of knowledge diffusion as participants are often required to disclose information on their intellectual property.

[10] The majority of important SSOs is included in our dataset. It is however limited with regards to the absence of standards from the SSO IETF.

[11] This has for instance been the case of the DVD format, which was first specified by an informal, ad-hoc industry group, and was eventually adopted as an ISO standard.

[12] In particular, we experimented with different adjustment procedures, i.e. using the distribution of standards with known complete date (instead of a uniform distribution) to allocate the standards with incomplete date, or using only the series for which the complete date is known. Results did not change.

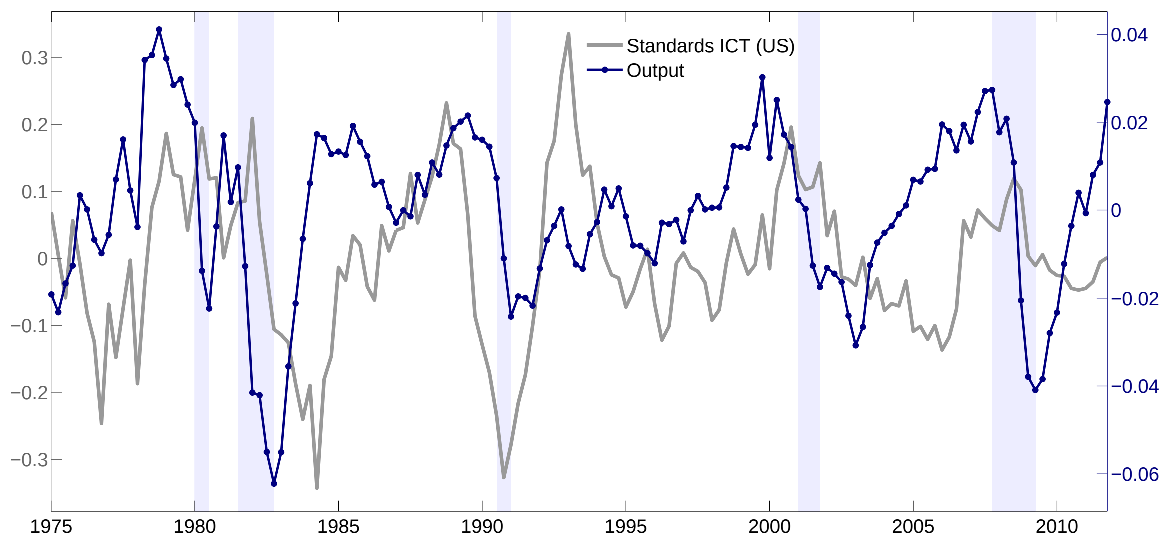
independently of the adjustment procedure. For details on the standards data, consult the data appendix.

Concerning macroeconomic variables, we will focus on the following series in the baseline version of our empirical model: output in the business sector, private fixed investment as well as total factor productivity (adjusted for capacity utilization). Extensions of the baseline model will include other macroeconomic variables: the S&P 500 stock market and NASDAQ Composite indices, consumption of goods and services, hours worked in the business sector, capacity utilization, price indices for investment and the Federal Funds rate. Data on macroeconomic aggregates are real, seasonally adjusted and transformed in per capita terms by dividing the series with the population aged 16 and above (taken from the BLS). All data are quarterly for the period 1975Q1–2011Q4. Detailed information on all the series, and in particular their sources, can be found in the appendix. For the estimations, all data series (but the Federal Funds rate) are in log levels.

3.2 Cyclical patterns

In figure 1, we plot the untreated data for standards in both the ICT sector and for all ICS classes. The standard series is substantially "lumpier" than typical macroeconomic series at this frequency. The standard series display very low, or even negative, autocorrelations. This is due to the fact that standardization is a process characterized by clustering and discrete action. By the very nature of standardization, a quarter that is characterized by a high standardization rate will be followed by a low standardization rate in the next quarter. The standardization series is a pure flow variable and not subject to the same degree of aggregation as typical macroeconomic series. Figure 1 also shows that the standard series for ICT and for all ICS classes differ substantially despite the former being part of the latter.

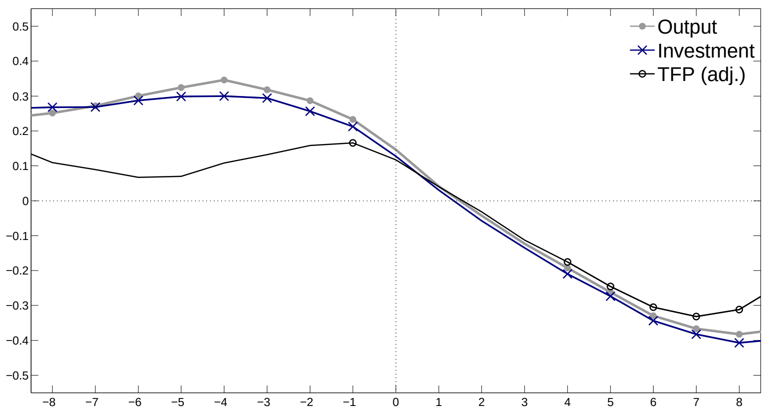
Figure 4: ICT Standards and business output



Notes: Data are in logs and HP-detrended (with smoothing parameter 1600). Output is seasonally adjusted. Standard data are smoothed over a centered window of 9 quarters. Shaded areas correspond to NBER recession dates.

One motivation for the analysis of the cyclical patterns of standardization is the fact that R&D and patenting have been found to be procyclical (Griliches, 1990; Barlevy, 2007; Ouyang, 2011). We explore the cyclicality of our new indicator and plot detrended non-farm business output as well as detrended and smoothed ICT standards[13] in figure 4 for the period 1975Q1 to 2011Q4. Clearly, the smoothed standard series shows a cyclical pattern as it moves along with the cycle or follows it with a lag of several quarters. This relation seems particularly pronounced during recessions.

Figure 5: Cross-correlations of ICT Standards and macroeconomic variables



Notes: The y-axis corresponds to the estimated cross-correlations of the standard series (s_t) and the respective macroeconomic variable (m_t), i.e. $\text{corr}(s_{t+k}, m_t)$ where k (in quarters) is plotted against the x-axis. Cross-correlations were calculated based on the data which are in logs, seasonally adjusted and HP-detrended. Standard data are smoothed over a centered window of 9 quarters. Markers indicate that the correlation is statistically different from zero (p-values smaller than 0.05).

Cross-correlations can give some information on the timing of this apparent procyclicality. Figure 5 shows that both output and investment lead our smoothed standardization series by four quarters. The correlation coefficient between output lagged by 4 quarters and the standard series amounts to 0.35 and is statistically different from zero. There is practically no correlation pattern at any lag of TFP adjusted for capacity utilization for its relation with standardization. Note that a significant cross-correlation with macroeconomic variables can only be established when the standard series is smoothed. This implies that procyclicality is characterizing the lower frequencies of the standard series. We will revisit this point when we investigate the cyclicality of the raw series in section 5.1. Though the smoothed standard series is lagging the cycle, this does not imply that technology does not impact macroeconomic variables. Causality can run in both directions: technological

[13]For this exercise we are interested in the exact timing of the standard release and therefore use the unadjusted standard series for which we know both the month and year of the release date. We detrend the standard series with a HP-filter and smooth the remaining high frequency movements since the standard series is very erratic. We do not apply a two-sided band-pass filter to the data as one would do for an erratic macroeconomic time series which is characterized by noise at high frequencies due to factors such as mismeasurement. In the case of our microeconomic standard series, however, discarding high frequency movements would be misleading as extreme values represent discrete technology adoption rather than mismeasurement. For the standardization data, we therefore smooth the detrended series using a simple moving average of window length of 9 quarters.

standardization is driven by the cycle but also generates a feedback on macroeconomic variables. To investigate the latter, we will need to extract the exogenous variation of standardization.

4 Econometric strategy

4.1 A Bayesian VAR which accounts for long diffusion lags

We are interested in the dynamic interaction between technology and the macroeconomic cycle and thus employ a vector autoregression model. Non-fundamentalness can arise in VAR models with news shocks or slow technology diffusion (Lippi and Reichlin, 1993; Leeper *et al.*, 2011). The appendix provides a discussion of this issue. One solution to the non-fundamentalness problem is to align the information set of the econometrician with the one of the agents which is the approach taken in this paper. We include 12 lags into the VAR – instead of the usual 4 lags that is often employed for quarterly data.[14] The choice of a generous lag length is motivated by the observation that slow technology diffusion might require a larger number of lags in order to ensure the unbiased estimation of the VAR coefficients.[15]

We use a Bayesian approach as it allows us to cope with overparameterization while still fully exploiting the information contained in longer lags of our technology variable. We impose a Minnesota prior, i.e. the prior coefficient matrix for macroeconomic variables mimics their unit root properties and the one for technology adoption assumes a white noise behaviour. The prior coefficients are as follows:

$$a_{ijl} = \begin{cases} \delta_i & \text{if } i = j \text{ and } l = 1 \\ 0 & \text{otherwise} \end{cases}$$

The parameter δ_i is set to one for non-stationary variables and to zero for stationary variables.

The informativeness of the prior is governed by the variance of the prior coefficients. A tighter variance implies that the coefficient of the posterior will more closely follow the prior coefficient. Tightening the prior variance, called "Bayesian shrinkage", allows us to deal with overparameterization as parameter uncertainty is reduced. The Minnesota prior assumes that longer lags are less relevant which is why they are shrunk to zero. This "'lag decay" is usually fixed *a priori* by the econometrician and uniform across all variables.

[14] Canova *et al.* (2010) also include 12 lags in order to avoid problems of non-fundamentalness and lag truncation as discussed below.

[15] This problem of "lag truncation bias" arises whenever the finite order VAR model is a poor approximation of the infinite order VAR model (see Ravenna, 2007 as well as Chari *et al.*, 2008). A finite order VAR, i.e. a VAR with a truncated lag structure, assumes that lags which are longer than the chosen lag length are zero. However, whenever there is slow diffusion and thus longer lags are non-zero, overly restrictive lag truncation leads to biased estimated coefficients. The true data-generating process is not well represented by a VAR with short lags. As a consequence, the estimated propagation matrix which defines the impulse response functions (IRFs) is biased despite the identification strategy being correct. Fève and Jidoud (2012) show that the inclusion of many lags considerably reduces the bias in VARs with news shocks. A similar point is raised by Sims (2012) who shows that the bias from non-fundamentalness increases with the anticipation lag of news shocks.

However, since the purpose of a generous lag length is to capture slow technology diffusion, we allow for variable-specific shrinkage of distant lags which we estimate from the data. By doing so, we want to avoid to forcefully shrink the influence of long lags of standards, but rather exploit the available information and "let the data speak". The informativeness of the prior, i.e. the variance of the prior coefficients, is therefore set as follows:

$$V\left(a_{ijl}\right) = \begin{cases} \dfrac{\phi_1}{l^{\phi_4}} & \text{for} \quad i = j,\ l = 1, \ldots, p \text{ (own lags, except standards)} \\ \dfrac{\phi_1 \phi_2}{l^{\phi_{4,j}}} \dfrac{\psi_i}{\psi_j} & \text{for} \quad i \neq j,\ l = 1, \ldots, p \text{ (lags of other variables)} \\ \phi_3 \psi_i & \text{for the constant} \end{cases}$$

The vector $\phi = (\phi_1\ \phi_2\ \phi_3\ \phi_4\ \psi_i)$ denotes the hyperparameters which govern the "tightness" of the prior. Note that, contrary to common set-ups, the lag decay governed by $\phi_{4,j}$ is variable-specific. The prior on the constant is assumed to be uninformative ($\psi_3 = 10^6$). The Minnesota prior is Normal-Wishart and thus requires a symmetric treatment of all equations (Kadiyala and Karlsson, 1997; Sims and Zha, 1998). Therefore, the hyperparameter ϕ_2 has to be set to one and the same lag decay for each variable is imposed on all equations. The scale parameters ψ_i can be estimated from the data with the procedure described below.

With ϕ_2 and ϕ_3 being fixed, we collect the remaining hyperparameters in the vector $\Theta = (\phi_1\ \phi_4\ \psi_i)$. The parameter ϕ_1 controls the overall shrinkage of the system. When $\phi_1 = 0$, the posterior distribution tends towards the prior distribution; on the contrary, when $\phi_1 = \infty$, the prior is flat and the posterior estimates coincide with the OLS estimates. Similarly, the lag decay parameter $\phi_{4,j}$ governs to which extent the coefficient on lag l of variable j in each of the equations is shrunk to zero. In setting Θ, we follow Canova (2007); Giannone *et al.* (2012b) and Carriero *et al.* (2011) and maximize the marginal likelihood of the data with respect to Θ. The marginal likelihood is given by

$$p(Y) = \int \int p(Y \mid \alpha, \Sigma)\, p(\alpha \mid \Sigma)\, p(\Sigma)\, d\alpha\, d\Sigma$$

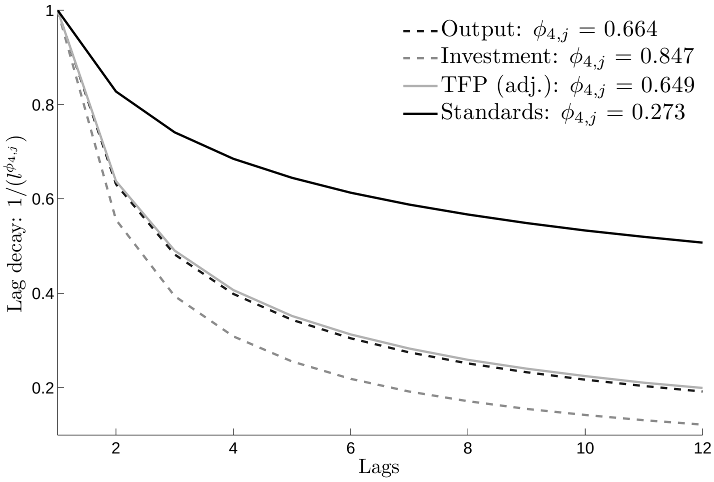
and is a function of Θ. The marginal likelihood integrates out the uncertainty of the parameters of the model. When we have no a priori information on the hyperparameters, the maximization of $p(Y)$ also leads to a maximization of the posterior of the hyperparameters and is thus equivalent to an Empirical Bayes method (Canova, 2007; Giannone *et al.*, 2012b). We then choose the overall shrinkage parameter Θ such that

$$\Theta^* = \arg\max_{\Theta} \ln p(Y)$$

The appendix describes the prior distributions, the posterior simulation and the selection of the hyperparameters in more detail.

The estimation of the lag decay of each variable is informative for evaluating the dynamics of the VAR system. In particular, the estimated lag decay parameter of each variable tells us whether long lags of each variable are important for the VAR system as a whole. Figure 6 displays the estimates of $\phi_{4,j}$ for the baseline model which includes output, investment, TFP and the standard series. Since this hyperparameter is an exponent, the differences across variables become most apparent when calculating the implied shrinkage directly (i.e. the inverse of the lag number to the power of the estimated $\phi_{4,j}$). The results

Figure 6: Lag decay estimates



Notes: The figure displays the estimates of the lag decay parameter and the implied shrinkage at different lag length for the four-variable baseline model. A higher value of $\phi_{4,j}$ implies a tighter shrinkage for distant lags, thus implying that these lags are not as important for the dynamics of the system.

confirm our assumptions from above. The prior variance for distant lags is considerably tighter for macroeconomic variables than for standards. This implies that long lags of the standard series are more important for the dynamics of the system than the ones of macroeconomic variables. This is consistent with the idea of slow technology diffusion that motivated our econometric approach.

4.2 Identification of shocks

When using a direct indicator of technological diffusion, it is important to specify what actually constitutes a technology shock. In general, business cycle economists summarize a large number of specific shocks under the term "technology shock". This is broadly defined as a shock that changes productivity which is why technology shocks are often associated with changes in Solow residuals. In the context of this paper, a technology shock is directly concerned with technological change, i.e. it is a shock to the distance between the technology frontier and currently adopted technology. This frontier is in turn a function of past investment in R&D and patenting (which are by themselves functions of the cycle) and a random science flow. The distance to the technology frontier is therefore partly exogenous and the catch-up via standardization captures this technology shock: whenever a very promising technology emerges, agents will want to standardize beyond of what the cycle would predict in the absence of this technology. We would like to stress that an identification based on standardization data is by definition concerned with a *specific type* of technology shock. This shock is orthogonal to reduced-form innovations in TFP which comprise other types of technology shocks such as managerial innovations or productivity-enhancing policy reforms.

We use a recursive (Cholesky) identification scheme to recover the structural technology shocks from the reduced-form errors. This approach is also used by Shea (1999) and Alexopoulos (2011) who identify technology shocks from patent data and technology manuals respectively. The literature on technology diffusion has shown that new technologies diffuse slowly. We should therefore expect the decision to catch-up with the technology frontier (our "technology shock") to impact standardization on impact, but not output, investment or TFP. A Cholesky identification scheme imposes minimal assumptions on the model. In contrast to the most commonly used identification schemes à la Galí (1999), we have direct access to an indicator of technology adoption and can thus exploit this data without imposing how technology shocks affect certain variables in the long-run. Moreover, by avoiding to rely on long-run restrictions, we make sure that we are not confounding technology shocks with any other shocks that have a permanent effect on macroeconomic variables.

In order to analyze the cyclicality of standardization (not smoothed as in section 3.2), we investigate its reaction to a "business cycle shock". This identification strategy follows Giannone *et al.* (2012a). A business cycle shock is defined as a linear combination of all the shocks in the VAR system which can explain the largest part of the variation of output at business cycle frequencies. This procedure is agnostic about the actual drivers of the business cycle shock which comprises underlying demand and supply side shocks. Nevertheless, it perfectly serves our purpose of identifying a shock which allows us to trace out the reaction of technology adoption to the cycle. Similar procedures using forecast error variance decompositions have been used by Barsky and Sims (2011) and Uhlig (2004). In particular, the "business cycle shock" is derived using frequency domain analysis and its detailed derivation is described in the appendix. We identify the business cycle and technology shocks simultaneously.

5 Discussion of results

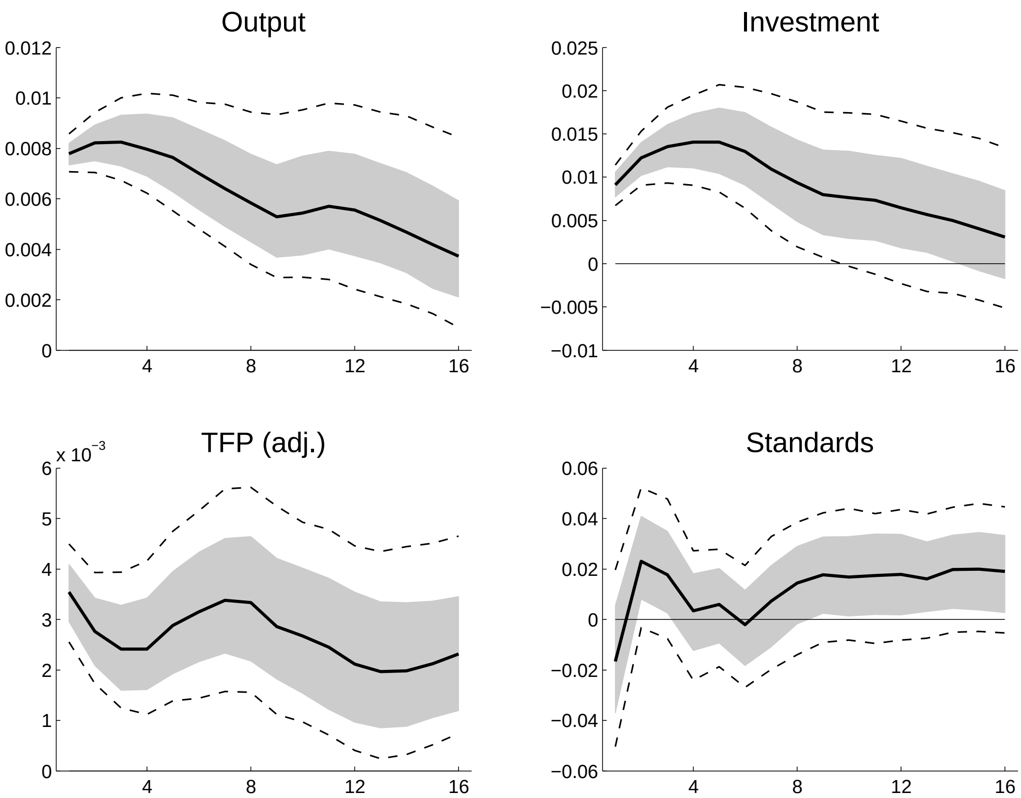
In this section, we present the results of our econometric analysis. In section 5.1, we further investigate the procyclicality of standard releases. In section 5.2, we study the effect of technology shocks on output, investment and TFP. Section 5.3 analyzes the signalling effect of technology standards by investigating the stock market response to technology shocks. We use information on standard characteristics in section 5.4 to investigate the differential impact of discontinuous and continuous technological change on macroeconomic variables.

5.1 Endogenous technology adoption

Papers studying the impact of innovative activity on macroeconomic variables often focus on long-run (growth) aspects, but neglect transitory dynamics and the impact on business cycles. While endogenous growth models endogenize technological progress as a decentral, cumulative process, RBC models typically assume an entirely *stochastic* technology supply. However, it is not straightforward why technology should be more exogenous than any other component of the cycle.

We therefore explore the reaction of standardization to cyclical movements in aggregate macroeconomic variables. Figure 7 displays the responses of standards to a business cycle shock and shows that technology *adoption* is also cycle-driven: the response of standardization to a business cycle shock is positive and significant in the short-run.

Figure 7: IRFs: Business cycle shock



Notes: Impulse responses to a business cycle shock identified as the shock that explains the maximum of the forecast error variance of output at business cycle frequencies (derivation to be found in the appendix). The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the distribution of impulse response functions and dotted lines denote the 5th and 95th percentiles. The unit of the x-axis is quarters.

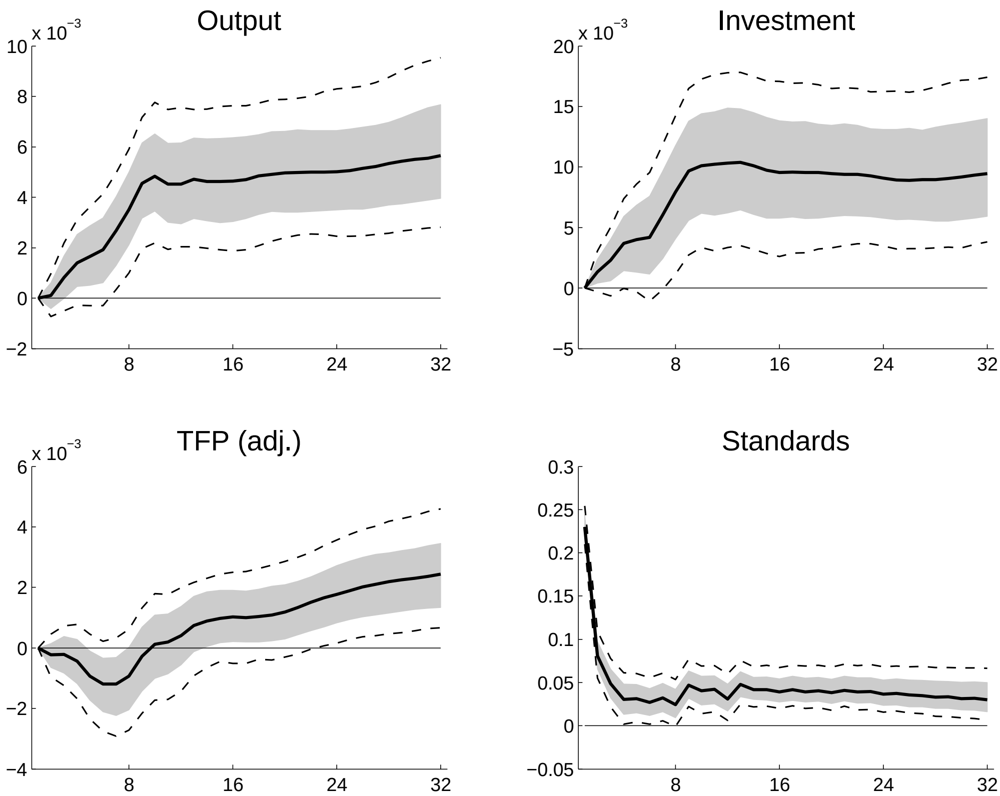
This result is in line with analyses of R&D spending and patenting which have consistently found that these measures are endogenous to macroeconomic variables (Barlevy, 2007; Ouyang, 2011; Aghion *et al.*, 2012; Griliches, 1990). Our findings also relate to the evidence presented in Geroski and Walters (1995) who show that technologies are adopted in clusters which coincide with economic booms. Procyclicality of standardization can mainly arise due to two effects. *First*, firms prefer to adopt technologies during economic upturns in order to profit from high demand. As such, entrepreneurs jointly delay adoption until the time of an economic boom to realize high rents as they fear imitation by competitors (Francois and Lloyd-Ellis, 2003; Shleifer, 1986). *Second*, the process of standardization is costly as firms need to invest in the adoption of new technologies, replace old standards and potentially increase human capital effort. For instance, Jovanovic (1995) shows that the costs for the implementation of new technologies exceed the research costs by a factor of 20. Credit-constrained firms could thus find it difficult to finance these costly investments in economic downturns.

5.2 Transitory dynamics following a technology shock

5.2.1 Impulse responses to technology shocks

The primary interest of this paper is to investigate the aggregate effects of technology shocks on the macroeconomic cycle. Figure 8 displays the impulse responses to our technology shock. We will first discuss the reaction of output and investment before turning to TFP further below.

Figure 8: IRFs: Responses to a technology shock



Notes: Impulse responses to a technology shock. The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the distribution of impulse response functions and dotted lines denote the 5th and 95th percentiles. The unit of the x-axis is quarters.

Effect of technology shocks on output and investment. The reaction of output and investment is positive and S-shaped. In particular, the reaction is sluggish immediately after the shock, picks up after 4–6 quarters and reaches its maximum after 10–12 quarters. The effect of the identified technology shock is permanent. This S-shape mirrors processes of technology diffusion analyzed in previous research (Griliches, 1957; Jovanovic and Lach, 1989; Lippi and Reichlin, 1994): technologies propagate slowly at first and then accelerate before the diffusion process finally levels off. Different technologies diffuse at different speed with estimates of adoption lags ranging from a few years to several decades with more recent inventions adopted faster than older ones (Comin and Hobijn, 2010). The effects of the type of technology adoption we measure in our setup materialize fully after 3 years.

Figure 8 also displays the response of standards. On impact, standardization peaks, but the response to the shock is not persistent. This is consistent with the idea that technology adoption is very lumpy as the catch-up with the technology frontier entails the bundled adoption of hitherto unadopted technologies. Once technologies are adopted in a quarter, the following quarter is characterized by low adoption rates.

In order to verify the validity of our technology indicator, we explore which sub-components of investment are affected the most. For the purpose of analyzing the effects on various sub-components, we estimate a BVAR where the variable representing the respective type of investment is block-exogenous to the remaining BVAR system. In particular, the estimated BVAR system consists of a first block which corresponds to the baseline model and a second block comprising one type of investment. The latter is assumed to have no impact on the variables in the first block at any horizon. This block exogeneity assumption ensures that the estimated BVAR coefficients of the first block remain the same as in the baseline model and that the technology shock is identified consistently across all investment components. We estimate a BVAR for each component that is added one-by-one to the baseline model. Details on the implementation of the block exogeneity VAR and its Bayesian estimation can be found in the appendix.

Table 2: Impact of a technology shock, IRF at horizon 16

Investment series	
Equipment	0.69*
Information processing equipment	1.37*
Computers and periphal equipment	3.43*
Other information processing equipment	0.45*
Industrial equipment	0.37
Transportation equipment	0.37
Other equipment	0.10
Intellectual property products	0.90*
Software	1.95*
Research and development	0.63*
Entertainment, literary, and artistic originals	0.34*

Notes: The table displays the value of the impulse response function of the identified technology shock in different investment types after 16 quarters. The identified technology shock is exactly the same as the one in the baseline model and its different effect on the respective sub-component of investment is estimated by imposing block exogeneity. "*" denotes significance at the 16th/84th percentile.

Table 2 lists the responses of several subcomponents of nonresidential private fixed investment after 16 quarters. The results in table 2 suggest that our indicator correctly picks up a technology shock as defined in this paper: the reaction of investment in computers and peripheral equipment exceeds the one of non-technological equipment by a factor of 9 approximately. The second largest reaction is the one by investment in software. Other types of investment react only to a considerably smaller extent than technology-intensive equipment and their response is not significant.

Note that the investment series in table 2 do not represent investment in different sectors, but rather different types of investment across all sectors of the economy. The estimates in table 2 therefore represent the diffusion of new technologies such as computers and software which can be expected to be used as input factors in a large variety of sectors.

Effect of technology shocks on TFP. We interpret our measure of technology adoption as an indicator of the introduction of new vintages of capital that differ in productivity from older vintages. Technology adoption is therefore a measure of *embodied* technological change. The impulse response of TFP measures to which extent the use of new vintages of capital translates into higher productivity.

Figure 8 shows that TFP falls in the first quarters following a technology shock. The results imply that an immediate pick-up of productivity cannot be taken for granted when a technology is adopted by firms. This finding thus runs counter to RBC-type approaches where technology shocks are assumed to lead to immediate increases in TFP. However, research in industrial organization and the vintage capital literature has shown that such a reaction is plausible: the introduction of a new technology can cause inefficiencies due to the incompatibility of the new technology with the installed base (Farrell and Saloner, 1986). This incompatibility concerns both human and organizational capital as well as physical capital. An important investment must be made in *incremental* innovation and in the construction of compatible physical and human capital in order to exploit the technological potential of the new *fundamental* technology (the standard). After a technology shock, TFP can therefore temporarily decrease, before the implementation and deployment of the new technology raises the level of productivity permanently.

The vintage capital literature has relied on the concept of incompatibility of new and existing technologies to explain temporary slowdowns in productivity (Hornstein and Krusell, 1996; Cooley *et al.*, 1997; Greenwood and Yorukoglu, 1997; Andolfatto and MacDonald, 1998). In particular, these models study the role of learning for the so-called "productivity paradox" in the light of the ICT revolution following Solow's diagnosis that "we can see the computer age everywhere but in the productivity statistics". Since our technology shock is identified using the general purpose technology ICT, the results confirm findings which have previously been found in the literature. Yorukoglu (1998) finds that the introduction of ICT requires a considerable investment into learning and stresses that it is in particular ICT capital which is characterized by a strong degree of incompatibility across different vintages. Samaniego (2006) stresses the need for reorganization at the plant level due to the incompatibility of new ICT technologies with existing expertise.

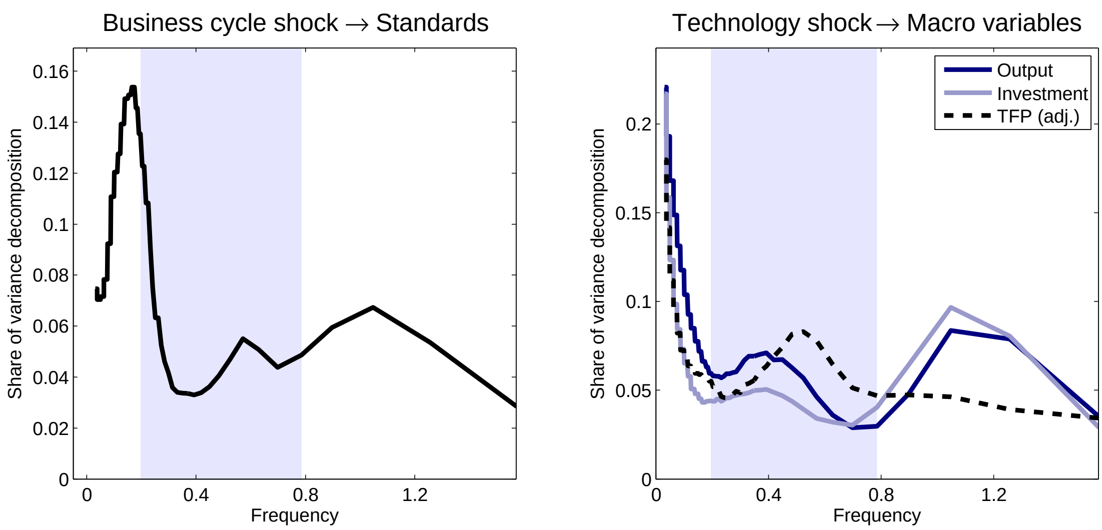
The impulse responses of TFP to technology shocks contrasts with earlier research. Using R&D and patent data to identify technological progress, Shea (1999) does not find a reaction of TFP to technology fluctuations at any horizon. Our analysis deviates from this earlier contribution, notably since we use an indicator directly related to the adoption, and not the development or invention of new technologies. The same argument is made by Alexopoulos (2011) who uses technology publications as a proxy for the implementation of new technologies. She finds that the reaction of TFP to technology shocks is positive and economically important; however, there is no short-term contraction as in our case. This contrasting result could be due to several factors. *First*, using quarterly instead of annual data, we are better able to identify short-term reactions. *Second*, we are concentrating on a general purpose technology which can necessitate organizational restructuring and learning. *Third*, the establishment of compatibility requirements via standardization identifies the fundamental first step in the process of adoption and might therefore be occurring prior to the introduction of technology manuals. Preceding the actual commercialization of a product, standardization first necessitates investment in complementary innovation and reorganization which is not picked up by the indicator in Alexopoulos (2011).

Our finding casts doubt on macroeconomic models which neglect the microeconomic mechanisms of technology adoption and simply assume an immediate pick-up of TFP following the introduction of a new technology. The results also show that TFP is rising in the long-run and thus confirm the productivity-enhancing role of technology adoption and its importance for long-run growth. Another implication of the above results concerns the temporal sequencing that technology adoption is subject to. Due to the requirement to standardize and the subsequent necessity to invest in incremental innovation, technology shocks might be anticipated. In this context, it is interesting to note that the response of TFP to a technology shock displays a strikingly similar shape as the reaction of TFP to the news shock identified by Beaudry and Portier (2006) – an issue we will turn to in section 5.3.

5.2.2 Quantitative importance of technology shocks

The early RBC literature attributed a very large share of variations in aggregate fluctuations to "technology shocks". The hypothesis of technology-driven business cycles has seen a revival with the vintage capital literature and in particular the literature on investment-specific technological (IST) change (Greenwood *et al.*, 1988, 2000; Fisher, 2006; Justiniano *et al.*, 2010). In order to analyze the relative importance of the two identified shocks in our model, we rely on forecast error variance decompositions. In particular, we compute these variance decompositions in the frequency domain. Decomposing the variances at different frequencies is instructive for understanding whether short-term or long-term components (or both) of the data are driven by the shocks. The results are displayed in figure 9 which displays the variance decompositions against different frequencies. Table 3 summarizes these results for business cycle and medium-term frequencies.

Figure 9: Variance decompositions for different frequencies



Notes: The variance decompositions refer to the VAR whose impulse responses are displayed in figures 7 and 8. The left panel displays the contribution of the business cycle shock to fluctuations of the standard series and the right panel describes the contribution of the identified technology shock to fluctuations of macroeconomic variables. The shaded region corresponds to business cycle frequencies. Frequencies below 0.2 correspond to the medium- and long-run (32–200 quarters) whereas the ones greater than 0.8 correspond to high-frequency fluctuations (< 8 quarters).

Our results indicate that the identified technology shock is not the primary cause of macroeconomic fluctuations, but its contribution is still economically sizeable. From both figure 9 and table 3, it is obvious that technology shocks play a more important role for output, investment and TFP at lower frequencies. Between 14% and 19% of the fluctuations of macroeconomic variables can be explained by our technology shock at medium-term frequencies; at business cycle frequencies, we are able to explain between 5% and 6%. This result is in line with what one would expect from growth theory: The introduction of a new technology causes gradual organizational changes in the short- and medium-run on the industry- and plant-level, but its aggregate effects on the macroeconomic cycle matter predominantly in the long-term.

The variance decompositions can be compared to previous research that relies on direct indicators of technological change. Whereas the R&D and patenting measures used by Shea (1999) hardly contribute to macroeconomic fluctuations, Alexopoulos (2011) finds that technology shocks identified from technology publications account for a considerable portion of GDP fluctuations (i.e. 10–20% after 3 years), with the contribution of technology shocks being more important at longer horizons. Basu *et al.* (2006) find that shocks identified from Solow residuals that are corrected for non-technology factors account for 17% of GDP fluctuations after 1 year and 48% after 10 years. These magnitudes, which are somewhat greater than ours, can be traced back to differences in scope and approach. While our identified shock should lead to movements in the measure constructed by Basu *et al.* (2006), other types of shocks might as well. This could explain the higher contribution of the latter.

The contribution of our identified technology shocks contrast with what is sometimes found in the IST literature. In this literature, the relative price of investment is used to assess the importance of IST shocks for business cycle fluctuations. Using predominantly estimated structural models, this literature finds that the contribution of IST shocks to aggregate volatility ranges from about 20% to 60%.[16] The fact that the identification of IST shocks and our technology shock differ substantially could imply that both are picking up different stages in the implementation of a new technology. In that respect, it is not straightforward to establish that our technology shock necessarily leads to an immediate decrease in the relative price of investment. In addition, compared to the narrowly defined technology shock that we are identifying, the conceptual interpretation of neutral technology or IST shocks is extremely broad. Neutral technology shocks are generally perceived as a "measure of our ignorance", but even the definition of IST shocks is not as clear-cut. In this respect, Justiniano *et al.* (2011) show that IST shocks are partially associated with financial frictions and not with technology improvements in their literal meaning.[17] This paper, on the contrary, identifies a precisely defined technology shock which is not a black box. Other "technology shocks" such as policy changes, organizational

[16] Greenwood *et al.* (2000) find that 30% of business cycle fluctuations can be attributed to IST shocks. A similar value of 50% is found by Justiniano *et al.* (2010). Smets and Wouters (2007) find somewhat smaller values, especially at longer horizons. Using structural VAR analysis, Fisher (2006) finds that 34% to 65% of output fluctuations are driven by IST shocks in the long-run whereas the contributions in the short-run are comparable to our results.

[17] In addition, identification of IST shocks via an endogenous measure such as the relative price of investment leaves room for other shocks (such as terms of trade shocks as shown by Basu and Thoenissen (2011))

restructuring or human capital can be equally or even more important for aggregate volatility. However, their propagation might be quite different which is why it is crucial to analyze them separately. Given that we are isolating a specific technology shock which is not a linear combination of several underlying types of technology shocks, the contribution of our technology shock to aggregate volatility appears to be economically sizeable.

Table 3: Variance decompositions at different frequencies

	Business cycle shock		Technology shock	
Frequency (quarters)	8–32	33–200	8–32	33–200
Output	0.47	0.17	0.06	0.19
Investment	0.27	0.10	0.05	0.14
TFP (adj.)	0.21	0.13	0.06	0.14
Standards	0.07	0.07	0.68	0.26

Notes: The table displays the contribution of the identified business cycle and technology shocks at business cycle frequencies (8–32 quarters) as well as over the medium- to long-run spectrum (33–200 quarters).

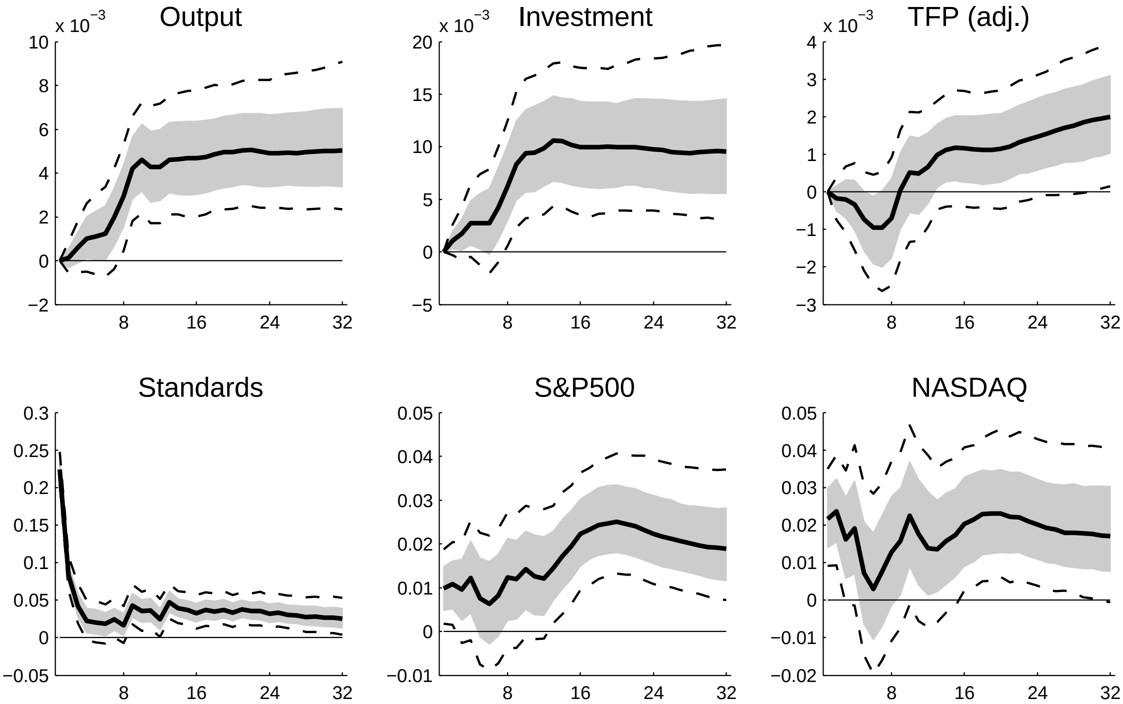
The results in figure 9 and table 3 also show that the business cycle shock mainly influences standardization at low frequencies which confirms the facts established in section 3.2. The very high frequency variation which characterizes the standard series is to a large extent generated by idiosyncratic movements. Macroeconomic shocks rather play a role for overall trends in technology adoption, but cannot account for the spikes in the standard series because technology adoption is by its very nature a lumpy decision. Our results relate to those of Comin and Gertler (2006) who show that, at the medium-term cycle (defined as the frequencies between 32–200 quarters), embodied technological change is procyclical.

5.3 Technological change and anticipation

Figure 8 shows that the effect of technology adoption on the cycle is characterized by slow diffusion. We identify an observable event which produces tangible effects only after several quarters. One of the reasons for these delays is that incremental innovation is needed to adapt a new technology to the specific needs of its users. This "time to implement" (Hairault *et al.*, 1997) causes slow diffusion, but agents nevertheless observe the initial shock. Standardization could therefore represent an important signalling mechanism.

Beaudry and Portier (2006) use stock price movements to identify news about the future and show that these precede an increase in TFP occuring several years later. The role of standardization as a prerequisite for the implementation of new technologies as well as the above results motivate the inclusion of stock market variables. This exercise is not only interesting due to the conceptual similarity of "news shocks" and slow technology diffusion, but is also instructive in order to verify if the above results hold in a system which includes forward-looking variables.

Figure 10: IRFs: Responses to a technology shock and news



Notes: Impulse responses to a technology shock. The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the distribution of impulse response functions and dotted lines denote the 5th and 95th percentiles. The unit of the x-axis is quarters.

We therefore add the NASDAQ Composite and S&P 500 indices to our VAR.[18] They are ordered last as we assume that news about technology adoption can be incorporated by financial markets on impact. Results are displayed in figure 10 which, first of all, shows that the findings from the earlier exercise (i.e. figure 8) are not affected by the inclusion of financial market variables. The impulse responses in figure 10 show that both the S&P500 as well as the NASDAQ Composite react positively to a technology shock. In particular, the reaction of the NASDAQ Composite, which mainly tracks companies in the technology sector, is more pronounced and significant on impact compared to the response of the more general S&P500. The reaction of the S&P500 and NASDAQ Composite indices confirm that financial markets pick up the positive news about future productivity increases despite the initial decline in TFP and the delayed response of output and investment.

We therefore interpret our technology shock as one that produces similar dynamics as a news shock. However, compared to an identification based on VAR innovations in stock prices (or TFP), our identified technology shock is orthogonal to those. Compared to the news shock literature, our shock explains a smaller share of aggregate volatility. Once again, this is due to the fact that we are isolating a very specific shock which comprises only a subset of the disturbances that "news shocks" comprise. Conceptually, our interpretation resembles the one of Comin *et al.* (2009) who model the idea of news shocks preceding

[18]The latter is added to the VAR as it is commonly used to identify news shocks as in the seminal contribution of Beaudry and Portier (2006). However, since we specifically want to focus on anticipation effects resulting from technology shocks, we also add a stock market index that captures developments in the field of technology as the NASDAQ does.

changes in TFP by explicitly associating expectations about the future with fundamental technological changes in a model of endogenous technology adoption.

The sign of the reaction of stock market variables to a technology shock is not straightforward. On the one hand, the value of existing capital decreases in response to the emergence of new technologies. Hobijn and Jovanovic (2001) show that the delayed implementation of new technologies causes the stock prices of existing capital to fall in the light of its future replacement by new capital. On the other hand, however, the prospect of future increases in productivity has a positive impact on current stock prices. Pástor and Veronesi (2009) find that large-scale adoption of new technologies can lead to initial surges in stock prices of innovative firms; news about the productivity-enhancing features of the new technology translate into positive movements of stock prices before these decrease eventually. In this paper, the response of stock market variables to a technology shock is very much in line with Comin *et al.* (2009): firms' stock prices not only reflect the value of installed capital, but also the discounted value of future capital, thus incorporating the expected increase in productivity from delayed technology adoption. Because the latter effect dominates, stock markets react positively.

5.4 Discontinuous vs. continuous innovation

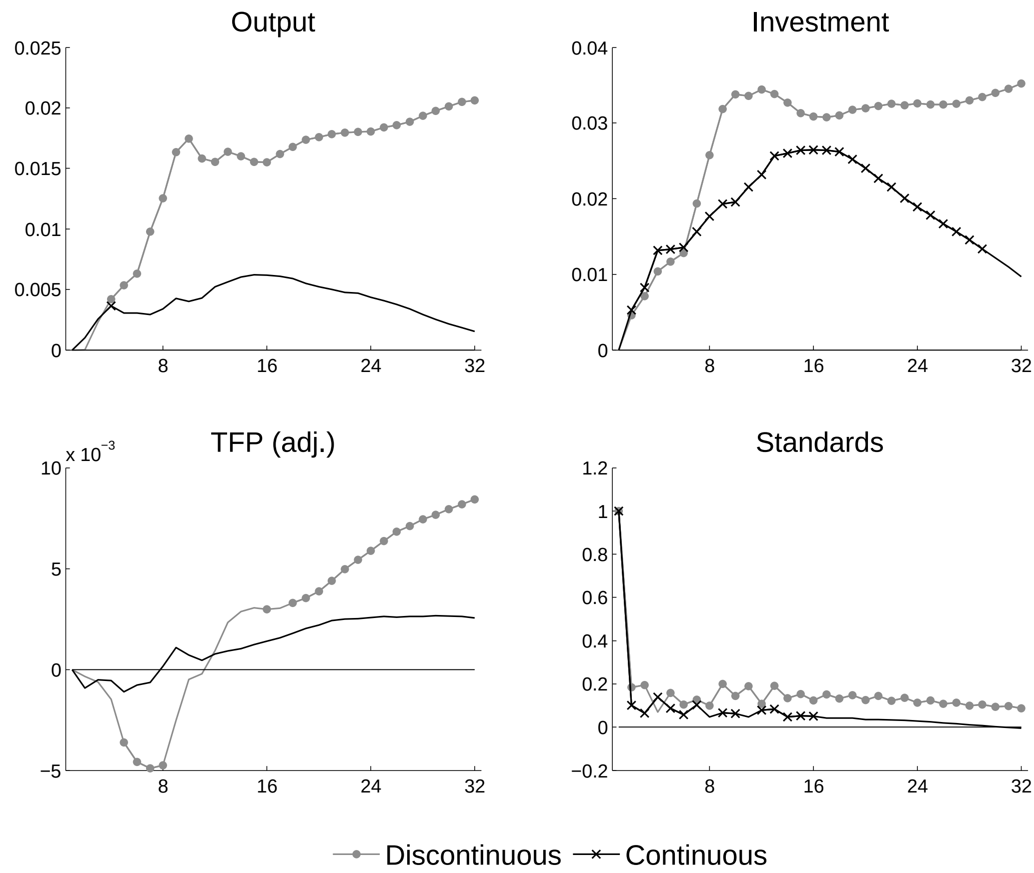
One of our main findings concerns the temporary decrease of TFP following a technology shock which we interpret as evidence for the incompatibility between new and existing technologies. In order to verify this interpretation, we use information on the version history of the standards in our dataset. Once a standard is issued, firms adopt it (gradually) and thus replace old vintages of a technology with a new one. The economic effect of a standard release depends on whether it is a new standard or whether it is an upgraded version of an already existing standard. We therefore construct two series, one which excludes upgraded versions of prior released standards from our standard count and one which only consists of upgraded versions.

We interpret the series of new standards as one that captures radical and discontinuous technologies. A *discontinuous* technological innovation is the starting point of a technological trajectory along which *continuous* innovations are constantly introduced until a new discontinuous technology emerges. Within the boundaries of their technological trajectories, standards can evolve through continuous upgrades and adjustments. We therefore interpret the standard series consisting of upgrades of already existing technologies as "incremental innovation".[19]

Figure 11 displays the reaction to a unit technology shock deduced from the different standard measures. The response of TFP is less pronounced and not significant for standard upgrades. New standards, however, provoke a negative and significant reaction of TFP in the short-run. This result can be related to the fact that a new standard defines a new technological basis which is often characterized by backwards non-compatibility. Short-term inefficiencies are more likely to arise when a new technology is introduced rather than when a continuous technology is implemented. The impulse responses in figure 11 also show that the response of investment is more persistent for the case of discontinuous

[19]Cf. Baron *et al.* (2013)

Figure 11: IRFs: Discontinuous vs. continuous innovation



Notes: Impulse responses to a technology shock. Crosses and circles denote that the response is significant at the 16th/84th percentile. The unit of the x-axis is quarters.

innovation than the one of continuous innovation. The introduction of a new standard necessitates substantial, costly investment into interoperability and new infrastructure; this process is very persistent. On the contrary, upgrades and continuous technological change provoke a more short-lived response of investment.

These results are also mirrored in the variance decompositions (table 4). The contribution of the discontinuous technology shock to macroeconomic fluctuations exceeds the one of continuous technological change by a factor of 2 to 3. This holds true for both business cycle and medium- to long-run frequencies. The difference is most pronounced for output and TFP whereas investment is driven to a similar degree by both continuous and discontinuous technical change. This is in line with our interpretation of discontinuous technology shocks representing investment into incremental innovation, despite the fact that their effect on output and TFP remains below the one triggered by discontinuous technology shocks.

Table 4: Variance decompositions: discontinuous vs. continuous technology shock

	Discontinuous		Continuous	
Frequency (quarters)	8–32	33–200	8–32	33–200
Output	0.06	0.19	0.02	0.07
Investment	0.05	0.14	0.03	0.10
TFP (adj.)	0.08	0.15	0.02	0.07
Standards	0.69	0.27	0.71	0.13

Notes: The table displays the contribution of the discontinuous and continuous technology shocks at business cycle frequencies (8–32 quarters) as well as over the medium- to long-run spectrum (33–200 quarters).

6 Extensions

6.1 Enlarging the definition of relevant standards

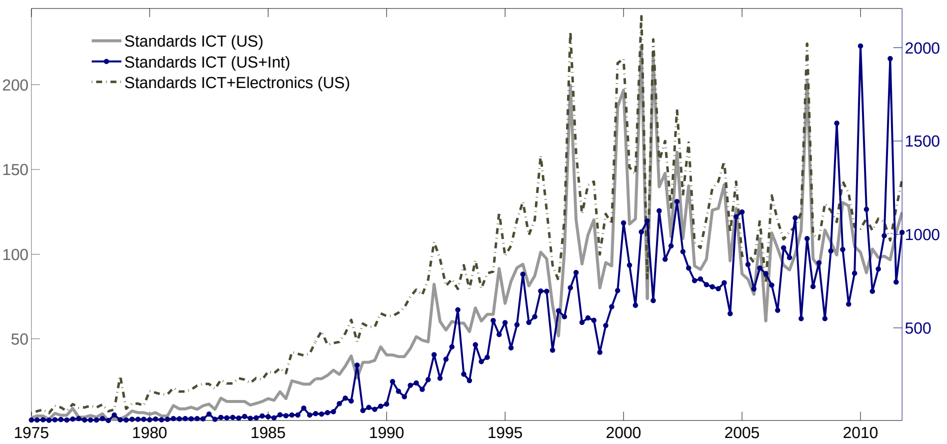
All results presented so far were obtained using a series of ICT standard documents released by US-based SSOs. In this section, we will analyze the robustness of our results by relaxing both the technological and the geographical definitions we used in computing our standard counts.

First, the US economy may also respond to standards released by non-US based SSOs, and in particular a number of SSOs with worldwide outreach (e.g. ISO). The most important and most relevant standards issued by these international bodies are generally accredited at US SSOs included in our sample (such as ANSI). Nevertheless, the documents issued by international SSOs largely outnumber standard documents issued by US SSOs, and include several well-known and fundamental technology standards in the area of ICT. We therefore compute a combined series counting ICT standards issued by both US and international SSOs. We remove duplicates resulting from multiple accreditations of the same document and always keep only the earliest date of standard release (details in the data appendix).

Second, technological advances in fields outside of, but closely related to ICT might also matter for aggregate volatility. This is for instance the case for the field of electronics, including semiconductors. We therefore compute a series of US standards releases in a wider technological field including information and telecommunication technologies, but also electronics and image technology (ICS classes 31 and 37).

We plot both these new series against the one including only ICT standards from US SSOs in figure 12. The plots show that there is a clearly positive correlation of the three series (in part due to the fact that one series includes the other); however, a large number of the spikes between international and US standards do not coincide. The correlation between the ICT standard count and standard count including both ICT and electronics (both from US SSOs) is stronger than the one between ICT standards from international and US SSOs.

Figure 12: ICT standard series 1975Q1–2011Q4

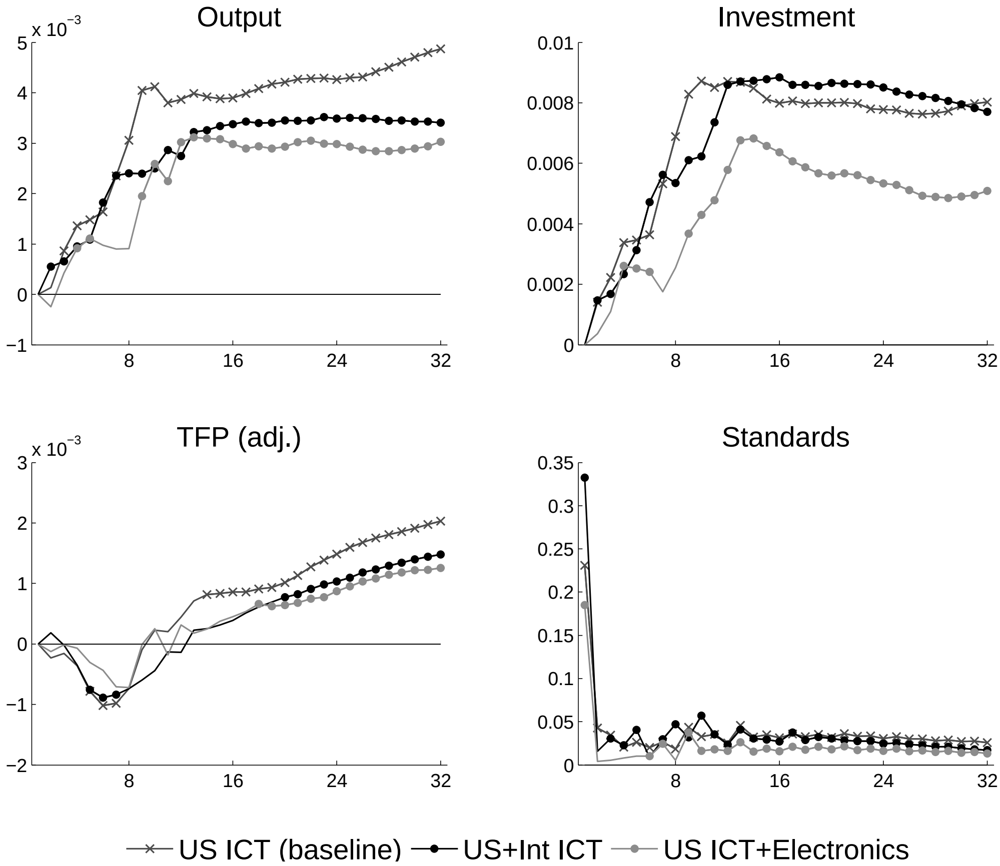


Notes: The series display the number of standard counts per quarter. The left-hand side y-axis corresponds to ICT standards (ICS classes 33-35) as well as ICT and electronics standards (ICS classes 31–37) which were released by US standard setting organizations over the period 1975Q1–2011Q4. The right-hand side corresponds to ICT standards released both by US and international standard setting organizations over the same period.

We use the new standard series to replicate the findings that we obtained using ICT standard documents of US SSOs. The IRFs from this robustness check are qualitatively and quantitatively very similar to the results presented so far (figure 13). We are therefore able to confirm our previous results with data series that include much larger numbers of documents and are substantially different in many aspects, but should pick up similar information.

Though the dynamics of impulse responses are very similar, the variance decompositions in table 5 show that the contribution of the technology shock identified from both US and international standardization data is smaller by a few percentage points. We interpret this difference as evidence that international standards may pick up phenomena unrelated to the actual adoption of new technologies (such as trade harmonization). Another explanation concerns the fact that international standards most relevant to the US were already included in the baseline series of US standards documents because they were accredited by at least one US SSO. As a corollary, the remaining standards in the international series are less important for technological progress in the US. The contribution to macroeconomic volatility of the technology shock identified with standards in the broader technological field is also smaller than the one induced by the more narrowly defined ICT standards. This finding provides further support for our strategy to concentrate on ICT, where technology adoption is most tightly related to standardization.

Figure 13: IRFs: Larger definitions of standard counts



Notes: Impulse responses to a technology shock. The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the distribution of impulse response functions and dotted lines denote the 5th and 95th percentiles. The unit of the x-axis is quarters.

Table 5: Variance decompositions: Technology shocks identified from different standard counts

	US+Int ICT		US ICT+Electronics	
Frequency (quarters)	8–32	33–200	8–32	33–200
Output	0.03	0.13	0.04	0.11
Investment	0.03	0.15	0.03	0.08
TFP (adj.)	0.05	0.11	0.03	0.08
Standards	0.80	0.17	0.64	0.19

Notes: The table displays the contribution of the technology shocks identified from standard counts using data from US and international SSOs as well as those US standards comprising ICS classes 31–37. The variance decompositions are computed at business cycle frequencies (8–32 quarters) as well as over the medium- to long-run spectrum (33–200 quarters).

6.2 Weighting standards by their relative importance

We are confronted with the fact that our standard series attributes the same importance to every single standard. As a first means to take into account the relative importance of individual standards, we use reference weights. Referencing denotes the explicit link to an already existing standard by ulterior standard documents. We construct a series where we count the number of references received by each standard (forward-references). The number of forward-references is a good indicator for the extent to which a standard is used in different applications because a standard references another standard only if the implementation of the referencing standard necessitates the implementation of the referenced standard. In order to compare the relevance of standards released at different points in time, we only count the references received within the first four years after standard release (and accordingly we are only able to use standard documents released up to 2009 for this analysis).

A second way to control for the importance of standards is to weigh them by the number of pages. The number of pages is a plausible indicator for the technological complexity of the standard. SSOs generally try to keep standards as short as possible. Any technological description included into a standard represents a compromise that all parties have to agree upon, and binds the implementers of a standard to a particular technological choice. The standard document thus represents the most restricted description of a technology that suffices to ensure interoperability. Against this background, we hypothesize that more voluminous standard documents describe more complex technologies.

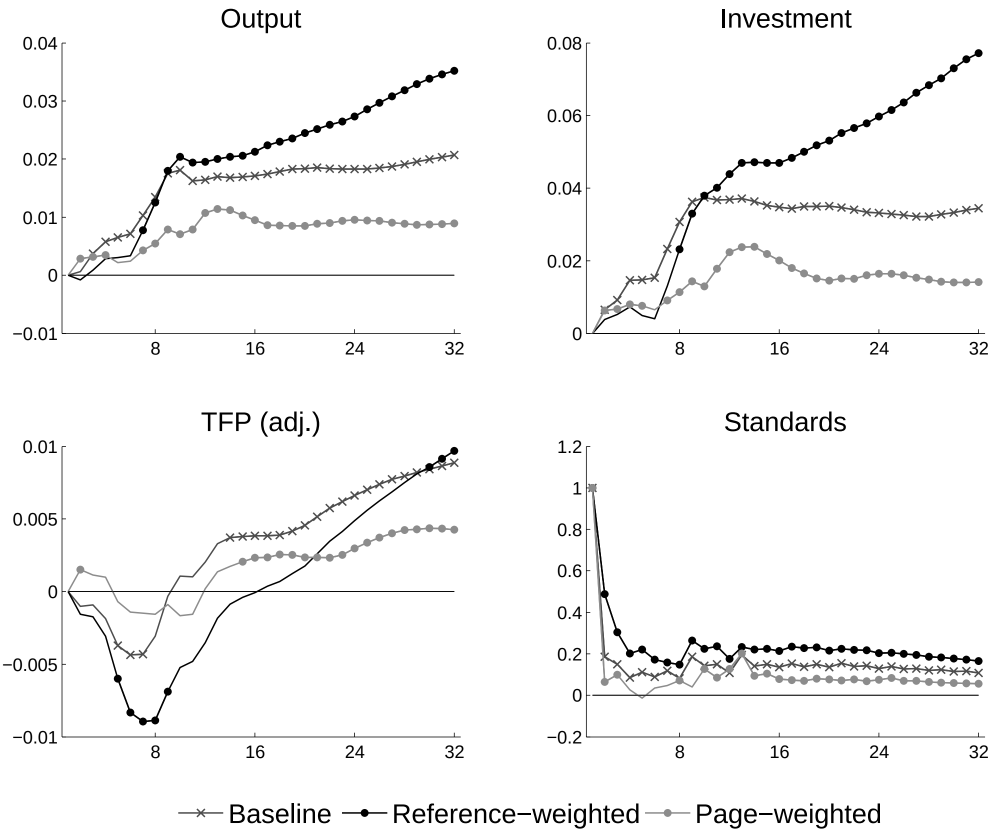
In particular, the two weighting schemes follow Trajtenberg (1990) who constructs citation-weighted patent counts. Similarly, we construct weighted standard counts (WSC):

$$\mathrm{WSC}_t^x = \sum_{i=1}^{n_t} (1 + x_{i,t}) \quad \text{where } x = r, p \tag{1}$$

where r denotes the number of references and p denotes the number of pages per standard i; n_t is the number of standards per quarter t. This measure thus assigns a value of one to every standard and reference/page.

Figure 14 displays the results of the baseline VAR system when ICT standards are replaced by the weighted time series counts (responses from the baseline model of figure 8 are displayed for comparison). We normalize the shock to one for better comparison. The results show that the dynamics hardly change in comparison to the impulse responses displayed in figure 8. The response of the reference-weighted series provokes a pronounced negative and significant response of TFP in the short-run, before picking up permanently. However, the response of TFP to innovations in the page count is not significant at short horizons. These findings are mirrored in the variance decompositions displayed in table 6. The contribution of the reference-weighted series is more important than the one using page-weights and even exceeds the ones from the baseline model. In general, we find that weighting standard documents by references is meaningful whereas this does not seem to be the case for pages. Complexity might therefore not necessarily translate into technological and economic importance.

Figure 14: IRFs: Different weighting schemes



Notes: Impulse responses to a technology shock using different ways to weigh the technological importance of a standard. "Reference-weighted" corresponds to the model where the standard time series is weighted by the number of references of the underlying standard and "page-weighted" corresponds to the weighting scheme using the page number of each standard. For the former, the model is estimated for the period 1975Q1–2009Q3 only. Crosses and circles denote that the response is significant at the 16th/84th percentile. The unit of the x-axis is quarters.

Table 6: Variance decompositions: technology shocks identified from reference- and page-weighted standards

	References		Pages	
Frequency (quarters)	8–32	33–200	8–32	33–200
Output	0.09	0.26	0.03	0.07
Investment	0.07	0.26	0.02	0.05
TFP (adj.)	0.12	0.27	0.04	0.05
Standards	0.70	0.33	0.64	0.12

Notes: The table displays the contribution of the technology shocks identified from reference- and page-weighted standard counts at business cycle frequencies (8–32 quarters) as well as over the medium- to long-run spectrum (33–200 quarters).

6.3 Larger VAR system

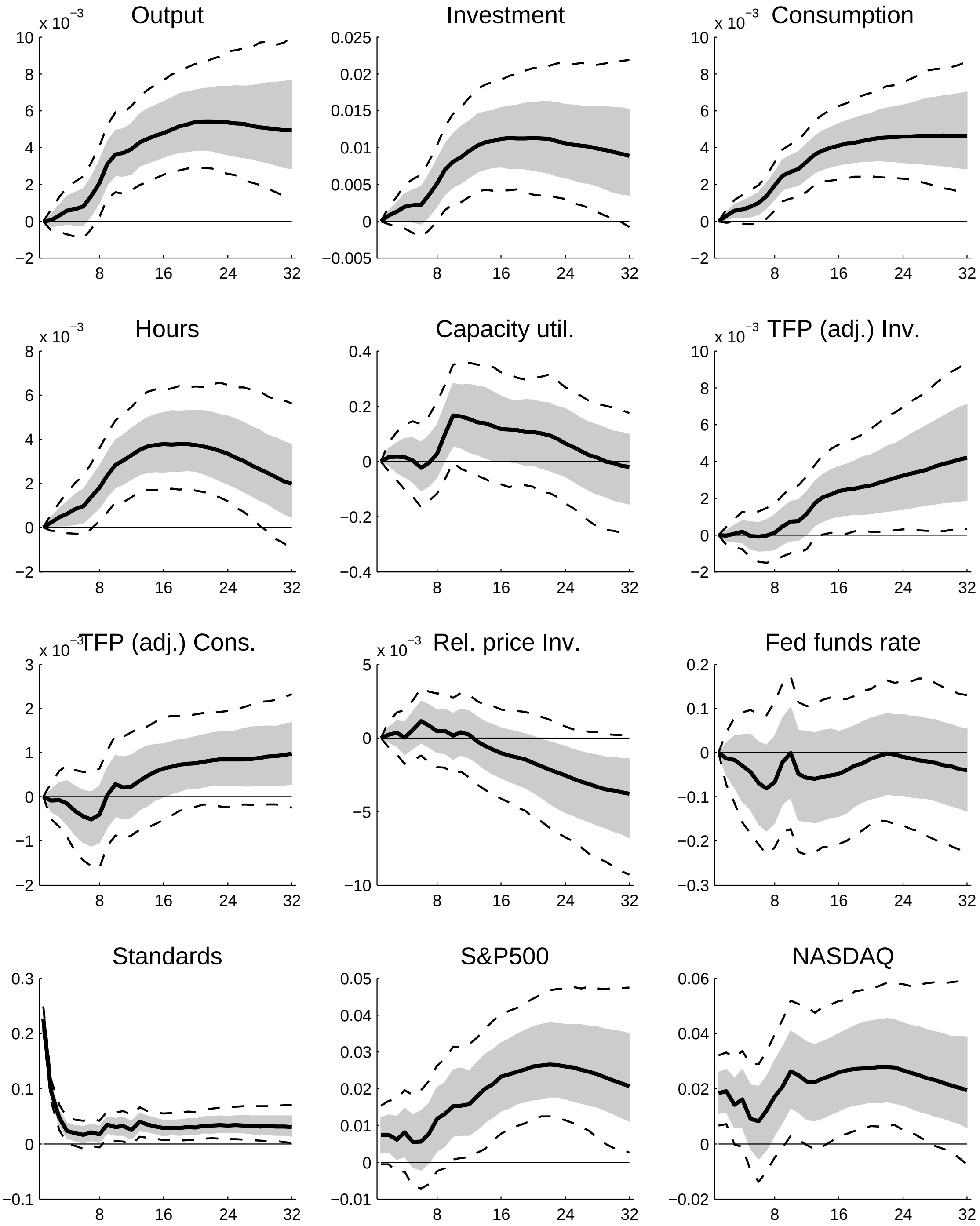
The Bayesian VAR approach allows us to include a large number of variables as the complexity of the system is automatically taken care of by the adjustment of the hyper-parameter ϕ_1. In order to verify the robustness of our results, we estimate a larger VAR system adding the following variables to the baseline model: consumption of goods and services, hours worked in the business sector, capacity utilization, the relative price of investment in equipment and software, the federal funds rate. TFP (adjusted for capacity utilization) is split into TFP in the investment goods sector as well as the consumption goods sector. As in section 5.3, we include stock market indices. We identify the technology shock as before and restrict the system to only allow for a contemporaneous reaction of standards and the stock market indices in response to a technology shock.

The results are displayed in figure 15. We first note that our results from the previous sections also hold in the larger system. Figure 15 shows that the identified technology shock produces comovement of output, hours, consumption and investment. In standard macroeconomic models where shocks trigger technological diffusion, wealth effects should lead to a decline in hours worked, investment and output as agents shift towards more consumption in the prospect of higher future productivity (Cochrane, 1994). However, if adoption is costly and requires training, a rise in labour *demand* reverses the effect on hours worked and investment since it requires more labour input and physical investment to implement new technologies whose higher productivity only materializes after several quarters. Regarding the *supply* of labour, the response of hours worked might be due to the fact that wealth effects on labour supply are actually nil or very small for the case of technology shocks.[20] At least in the short-run, this seems a plausible explanation as the introduction of new technologies is nevertheless associated with a lot of uncertainty regarding the timing and magnitude of future productivity improvements; intertemporal substitution effects might thus play a smaller role.

The results in figure 15 also demonstrate that capacity utilization rises until the technology shock has fully materialized. This is in line with the IST shock literature (i.e. Greenwood *et al.*, 2000) where a positive shock leads to a higher rate of utilization of existing capital: the marginal utilization cost of installed capital is lowered when its relative value decreases in the light of technologically improved new vintages of capital. Once technology has fully diffused (output, investment and consumption are at a permanently higher level), capacity utilization and hours decline again. The relative price of investment decreases following a technology shock but only does so after several years. This implies that our identified technology shock might nevertheless be conceptually different or timed differently than IST shocks. The effect of a technology shock on the Federal Funds rate is nil. As before, stock market indices react on impact, with the reaction being stronger for the NASDAQ than for the S&P500.

[20] This would be the case when Greenwood-Hercowitz-Huffman (GHH) preferences prevail — a point stressed by Jaimovich and Rebelo (2009).

Figure 15: IRFs from large model

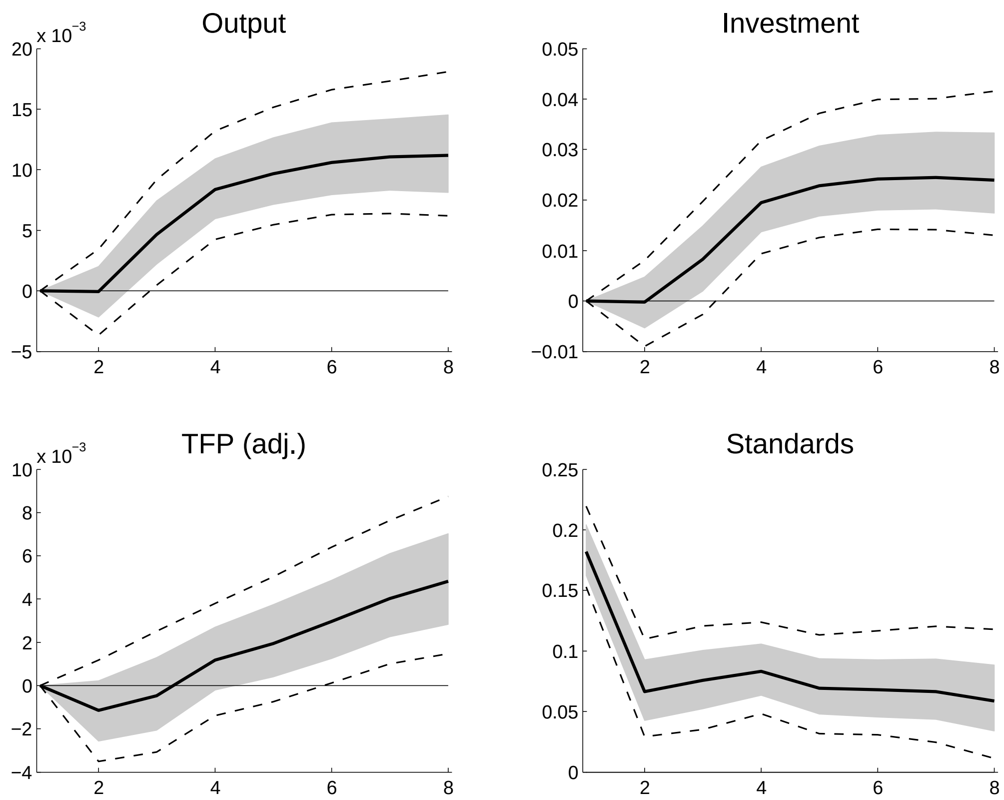


Notes: Impulse responses to a technology shock. The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the distribution of impulse response functions and dotted lines denote the 5th and 95th percentiles. The unit of the x-axis is quarters.

6.4 Annual data

For some of the standards in our dataset, information on the date of release only includes the year, but not the month of the release. In a last step, we want to test whether the fact that we distributed these standards uniformly across the quarters of the respective release year affects our results. We therefore construct annual count data for each of the standard series. We estimate a Bayesian VAR as before, using 3 lags (corresponding to the 12 lags used above for quarterly data) and determining the hyperparameters of the model as described in section 4.1.

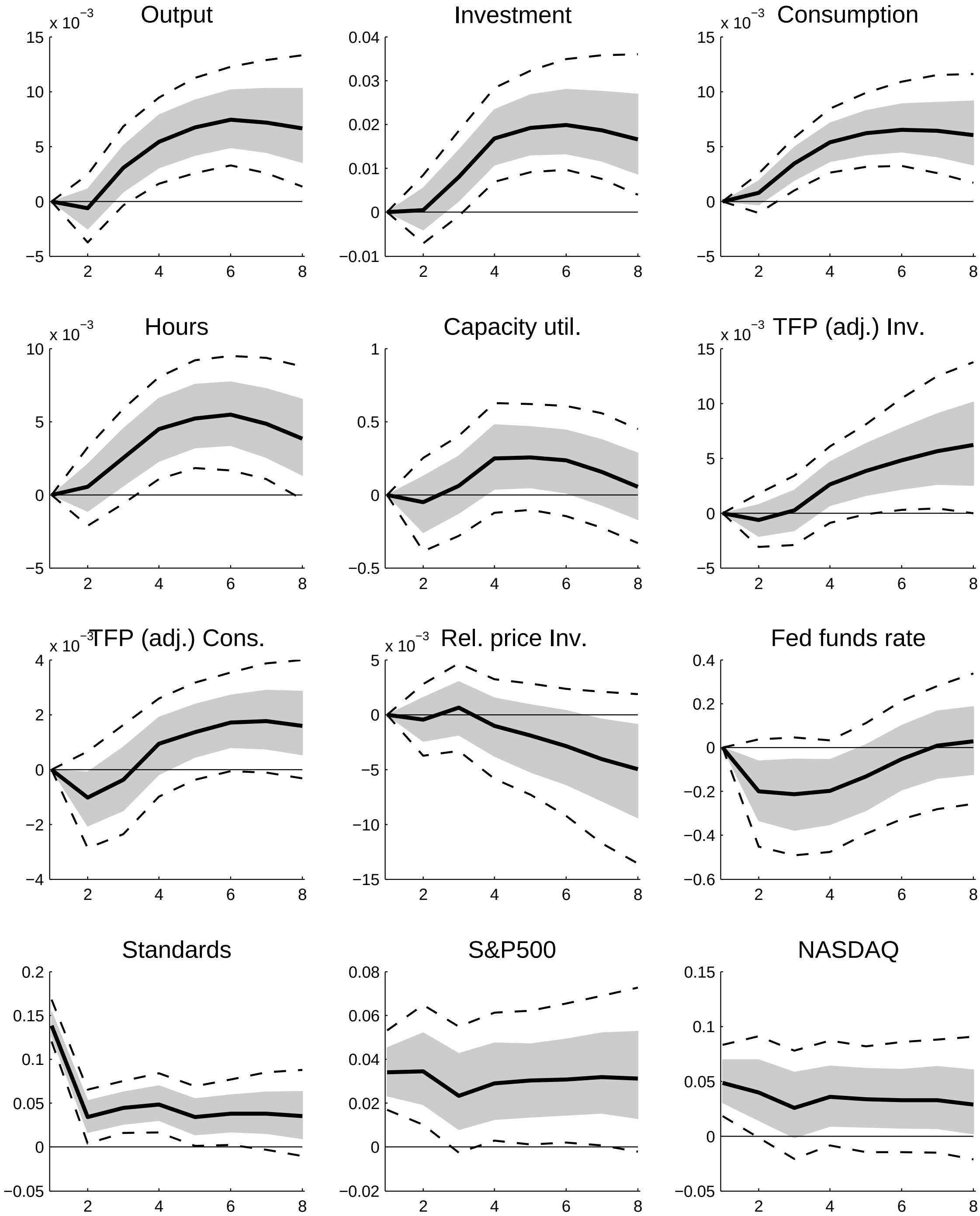
Figure 16: IRFs from baseline model: Annual data



Notes: Impulse responses to a technology shock. The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the distribution of impulse response functions and dotted lines denote the 5th and 95th percentiles. The unit of the x-axis is quarters.

The responses from the model estimated with annual data are strikingly similar to the ones from quarterly data. The responses of output and investment in figure 16 are clearly S-shaped. Whereas there is practically no reaction of output and investment during the first year following the shock, there is a clear increase in the following two years after which this expansion levels off. We also find the same short-term reaction for TFP as before: the median of the posterior distribution of impulse responses two years after the shock is negative before turning positive thereafter. In the long-run, TFP is increasing markedly.

Figure 17: IRFs from large model: Annual data



Notes: Impulse responses to a technology shock. The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the distribution of impulse response functions and dotted lines denote the 5th and 95th percentiles. The unit of the x-axis is quarters.

The dynamics of the baseline model are again confirmed in the larger model (figure 17). Output, investment, consumption and hours comove and are S-shaped. TFP decreases in the short-run before picking up after several years. The relative price of investment decreases in the long-run. Interestingly, the federal funds rate decreases. Stock market variables react on impact as before.

7 Conclusion

This paper analyzes the role of technology shocks for macroeconomic fluctuations. Its main contribution is to explicitly embed a microeconomic mechanism into the macroeconomic analysis of technology. The complex interdependencies of various technologies necessitate the coordinated establishment of rules. This process of technological standardization is a vital step for technology adoption. We therefore use the number of standard releases as a meaningful indicator grounded in innovation economics to investigate the interaction between technology and the macroeconomic cycle.

Our results contrast with previous findings and challenge several assumptions on technology that are widely used in macroeconomic research. Business cycle theories generally conceive technology to be an exogenous process. In these models, positive technology shocks translate into movements of macroeconomic variables on impact, in particular into immediate increases in TFP. In this paper, we draw a picture that is more in line with the microeconomic concept of technology: adoption is procyclical, technology diffuses slowly and its effects only materialize after considerable delay.

Though we isolate a very specific shock out of a large collection of shocks that usually constitute "technology" in macroeconomic models, its contribution to aggregate volatility is non-negligible; yet, it matters more at the medium-term horizon than in the short-run. We show that our identified technology shock generates an S-shaped response of output and investment as is typical of technological diffusion. Regarding the transitory dynamics of shocks to embodied technological change, we show that technology leads to an increase in productivity in the long-run, but the very nature of new technologies (and in particular discontinuous ones) can cause TFP to decrease in the short-run. We can therefore reconcile the fact that productivity slowdowns are observed in the data with the notion of a technology frontier which nevertheless increases constantly.

Our results also help to gain insights about the nature of shocks such as the ones found in the "news shock" literature. These news shocks are hardly linked to their specific underlying causes. Slow technological diffusion is characterized by similar propagation dynamics as news shocks. This paper shows that standardization is a trigger of technological diffusion and acts as a signalling device which informs agents about future macroeconomic developments. It is for this reason that forward-looking variables such as stock market indices, and in particular the NASDAQ Composite index which tracks high-tech companies, can react to a technology shock on impact.

Overall, this paper stresses the importance of looking into the microeconomic mechanisms that constitute the basis of the driving forces of macroeconomic fluctuations. Using the insights from the literature on industrial organization and innovation should help macroeconomists in opening the black box that technology and productivity often represent. Understanding the different dimensions of technological progress and disembodied productivity is ultimately a necessary condition for uncovering the different channels which impede and foster economic growth.

Appendix

A. Identification of a business cycle shock using frequency domain analysis

A business cycle shock is identified as in Giannone *et al.* (2012a) which adapts the identification strategy of DiCecio and Owyang (2010). This appendix largely follows the notation of Altig *et al.* (2005) who analyze the quantitative impact of various shocks on the cyclical properties of macroeconomic variables.

The structural moving-average representation of Y_t is

$$Y_t = D(L)\varepsilon_t \quad \text{where} \quad D(L) = \sum_{k=0}^{\infty} D_k L^k$$

where L represents the lag operator. Inverting $D(L)$ yields:

$$F(L)Y_t = \varepsilon_t \quad \text{where} \quad F(L) = B_0 - \sum_{k=1}^{\infty} B_k L^k = B_0 - B(L)$$
$$B_0 Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + \varepsilon_t$$

The reduced-form VAR model

$$Y_t = A(L)Y_t + u_t \quad \text{where} \quad E[u_t u_t'] = \Sigma \quad \text{and} \quad A(L) = \sum_{k=1}^{\infty} A_k L^k$$

relates to the structural representation as follows:

$$\begin{aligned} Y_t &= (B_0)^{-1}B(L)Y_t + (B_0)^{-1}\varepsilon_t \\ &= A(L)Y_t + u_t \qquad \text{where} \quad A(L) = (B_0)^{-1}B(L) \quad \text{and} \quad u_t = (B_0)^{-1}\varepsilon_t \\ &= [I - A(L)]^{-1} CC^{-1}u_t \quad \text{where} \quad C = (B_0)^{-1} \\ &= [I - A(L)]^{-1} C\varepsilon_t \qquad \text{where} \quad \varepsilon_t = C^{-1}u_t \quad \text{and} \quad E[\varepsilon_t \varepsilon_t'] = B_0 \Sigma B_0' = I \end{aligned}$$

In practice, a VAR of lag order p is estimated; hence, the infinite-order lag polynomial $A(L)$ is approximated by a truncated version $\sum_{k=1}^{p} A_k L^k$ of order p. The matrix B_0 maps the reduced-form shocks into their structural counterparts. Identification of the structural shocks can be achieved using various strategies such as short-run and long-run restrictions. Using a recursive Cholesky identification scheme, the variance-covariance matrix of residuals of the reduced-form VAR, Σ, can be decomposed in order to restrict the matrix C:

$$\Sigma = CC' \quad \text{and} \quad C = \text{chol}(\Sigma)$$

The identification of a business cycle shock is achieved by extracting a shock process which is a linear combination of all the shocks in the VAR system (except the technology shock) that leads to a high variation in output at business cycle frequencies. The identification of the technology shock, the column corresponding to the standardization variable, is left unchanged and identified via the standard Cholesky approach. In order to achieve the simultaneous identification of the technology and the "business cycle shock", a set of column vectors of C is rotated so that the shock $\varepsilon_{j,t}$ maximizes the forecast error variance of one of the variables $Y_{k,t}$ of the vector Y_t at business cycle frequencies. In the present case, the variable $Y_{k,t}$ corresponds to output. We denote the rotation matrix by R and can re-write our structural VAR accordingly:

$$Y_t = [I - A(L)]^{-1} CRR^{-1}C^{-1}u_t = [I - A(L)]^{-1} CR\varepsilon_t^* \quad \text{where} \quad \varepsilon_t^* = R^{-1}C^{-1}u_t$$

The variance of Y_t can be defined in the time domain:

$$E[Y_t Y_t'] = [I - A(L)]^{-1} CRR'C' [I - A(L)']^{-1}$$

Deriving its equivalent representation in the frequency domain requires the use of spectral densities. The spectral density of the vector Y_t is given by:

$$S_Y(e^{-i\omega}) = \left[I - A(e^{-i\omega})\right]^{-1} CRR'C' \left[I - A(e^{-i\omega})'\right]^{-1}$$

The spectral density due to shock $\varepsilon_{t,j}$ is equivalently:

$$S_{Y,j}(e^{-i\omega}) = \left[I - A(e^{-i\omega})\right]^{-1} CRI_jR'C' \left[I - A(e^{-i\omega})'\right]^{-1}$$

where I_j is a square matrix of zeros with dimension equal to the number of variables and the j-th diagonal element equal to unity. The term $A(e^{-i\omega})'$ denotes the transpose of the conjugate of $A(e^{-i\omega})$. We are interested in the share of the forecast error variance of variable $Y_{k,t}$ which can be explained by shock $\varepsilon_{t,j}$. The respective variances are restricted to a certain frequency range $[a, b]$. The ratio of variances to be maximized is then:

$$V_{k,j} = \iota_k' \frac{\int_a^b S_{Y,j}(e^{-i\omega})d\omega}{\int_a^b S_Y(e^{-i\omega})d\omega} \iota_k$$

where ι_k is a selection vector of zeros and the k-th element equal to unity. For business cycle frequencies with quarterly data, the frequency range $a = \frac{2\pi}{32}$ and $b = \frac{2\pi}{8}$ is used. The integral can be approximated by

$$\frac{1}{2\pi} \int_{-\pi}^{\pi} S(e^{-i\omega})d\omega \approx \frac{1}{N} \sum_{k=-\frac{N}{2}+1}^{\frac{N}{2}} S(e^{-i\omega_k}) \quad \text{where} \quad \omega_k = \frac{2\pi k}{N}$$

for a sufficiently large value of N. The contribution of shock ε_j to the forecast error variance of variable $Y_{t,k}$ at certain frequencies is consequently determined by:

$$V_{k,j} = \iota_k' \frac{\sum_{k=N/a}^{N/b} S_{Y,j}(e^{-i\omega_k})}{\sum_{k=N/a}^{N/b} S_Y(e^{-i\omega_k})} \iota_k$$

The identification consists in finding the rotation matrix R such that $V_{k,j}$ is maximized.

B. Details on the BVAR with a Normal-Wishart prior

Let us write our reduced-form VAR system as follows:

$$\begin{aligned} Y_t = X_t A + u_t \quad \text{where} \quad E[u_t u_t'] &= \Sigma \\ u_t &\sim \mathcal{N}(0, \Sigma) \\ \text{vec}(u_t) &\sim \mathcal{N}(0, \Sigma \otimes I_{T-p}) \end{aligned}$$

X_t comprises the lagged variables of the VAR system and A denotes the coefficient matrix. The Normal-Wishart conjugate prior assumes the following moments:

$$\begin{aligned} \Sigma &\sim \mathcal{IW}(\Psi, d) \\ \alpha = \text{vec}(A) \mid \Sigma &\sim \mathcal{N}(a, \Sigma \otimes \Omega) \end{aligned}$$

The prior parameters a, Ω, Ψ and d are chosen to ensure a Minnesota prior structure. The literature has usually set the diagonal elements of Ψ, ψ_i, proportional to the variance of the residuals of a univariate $AR(p)$ regression: $\psi_i = \sigma_i^2(d-k-1)$ where k denotes the number of variables. This ensures that $E(\Psi) = \text{diag}(\sigma_1^2, \ldots \sigma_k^2)$ which approximates the Minnesota prior variance. Following Giannone *et al.* (2012b), one can treat the diagonal elements of Ψ as hyperparameters in order to ensure that a maximum of the prior parameters is estimated in a data-driven way. For the Wishart prior to be proper, the degrees of freedom parameter, d, must be at least $k+2$ which is why we set $d = k+2$.

This paper generalizes the Minnesota approach by allowing for a variable-specific lag decay. Since ϕ_4 varies by each variable, we denote it by $\phi_{4,j}$. It can be shown that a Minnesota prior structure with variable-specific lag decay is imposed if the diagonal elements of Ω are set to $(d-k-1)\phi_1/(l^{\phi_{4,j}}\psi_j)$. As a result, the prior structure writes as follows:

$$\alpha_{ijl} \mid \Sigma \sim \mathcal{N}\left(a_{ijl}, \frac{\phi_1}{l^{\phi_{4,j}}}\frac{\psi_i}{\psi_j}\right) \quad \text{with} \quad a_{ijl} = \begin{cases} \delta_i & \text{if } i = j \text{ and } l = 1 \\ 0 & \text{otherwise} \end{cases}$$

The above expression shows that the Normal-Wishart prior maps into a Minnesota design with the particularity of ϕ_2 being equal to one and ϕ_4 being variable-specific. We have to impose $\phi_2 = 1$ due to the Kronecker structure of the variance-covariance matrix of the prior distribution which imposes that all equations are treated symmetrically; they can only differ by the scale parameter implied by Σ (see Kadiyala and Karlsson, 1997; Sims and Zha, 1998). As a corollary, the lag decay parameter $\phi_{4,j}$ can be specific to variable j, but cannot differ by equation i.

Since the prior parameters a, Ω, Ψ and d are set in a way that they coincide with the moments implied by the Minnesota prior, they thus depend on a set of hyperparameters Θ which comprises ϕ_1, $\phi_{4,j}$ and ψ_i (ϕ_2 and ϕ_3 are fixed). Integrating out the uncertainty of the parameters of the model, the marginal likelihood conditions on the hyperparameters Θ that define the prior moments. Maximizing the marginal likelihood with respect to Θ is equivalent to an Empirical Bayes method where parameters of the prior distribution are estimated from the data. The marginal likelihood is given by

$$p(Y) = \int\int p(Y \mid \alpha, \Sigma)\, p(\alpha \mid \Sigma)\, p(\Sigma)\, d\alpha\, d\Sigma$$

and analytical solutions are available for the Normal-Wishart family of prior distributions (see Giannone *et al.*, 2012b for an expression and a detailed derivation).

Maximizing the marginal likelihood (or its logarithm) yields the optimal vector of hyperparameters:

$$\Theta^* = \arg\max_{\Theta} \ln p(Y)$$

Giannone *et al.* (2012b) adopt a more flexible approach by placing a prior structure on the hyperparameters themselves. The procedure used in this paper, however, is equivalent to imposing a flat hyperprior on the model.

The original Minnesota prior assumes that the variance-covariance matrix of residuals is diagonal. This assumption might be appropriate for forecasting exercises based on reduced-form VARs, but runs counter to the standard set-up of structural VARs (Kadiyala and Karlsson, 1997). Moreover, impulse response analysis requires the computation of non-linear functions of the estimated coefficients. Thus, despite the fact that analytical results for the posterior of the Minnesota prior are available, numerical simulations have to be used.[21] Every draw of the matrix which maps the reduced-form innovations into structural shocks is taken from the draws of the posterior distribution of the model parameters; the identifying assumptions therefore reflect parameter uncertainty. Hence, we implement a Normal-Wishart prior where the prior mean and variance is specified as in the original Minnesota prior and we simulate the posterior using the Gibbs sampler. More specifically, the prior is implemented by adding dummy observations to the system of VAR equations. The weight of each of the dummies corresponds to the respective prior variance.

C. Implementing block exogeneity

In section 5.2, we implement a block exogeneity VAR. The purpose of this exercise where we add sectoral investment series one by one to the baseline VAR is to ensure that the technology shock is identified as in the baseline model. This appendix describes the estimation procedure which follows Zha (1999).

The structural model can be split in several blocks. Since we are working with two blocks in section 5.2, the following illustration concentrates on this case; but the exposition also holds for the general case of several blocks (see Zha, 1999).

$$\begin{pmatrix} F_{11}(L) & F_{12}(L) \\ F_{21}(L) & F_{22}(L) \end{pmatrix} \begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

[21]For structural VAR analysis, two approaches are commonly used (Canova, 2007): (1) A prior is imposed on the reduced-form coefficients and augmented by a Normal-Wishart prior whenever the VAR is exactly identified as in the case of Cholesky decomposition. (2) Whenever there is over-identification, Sims and Zha (1998) propose putting a prior on the structural coefficients directly. Restrictions on the structural parameters are also provided by the algorithm developed by Waggoner and Zha (2003).

The above model can be normalized by premultiplying it with the block-diagonal matrix of the contemporaneous impact coefficients:

$$\begin{pmatrix} B_{0,11}^{-1} & 0 \\ 0 & B_{0,22}^{-1} \end{pmatrix} \begin{pmatrix} F_{11}(L) & F_{12}(L) \\ F_{21}(L) & F_{22}(L) \end{pmatrix} \begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} B_{0,11}^{-1} & 0 \\ 0 & B_{0,22}^{-1} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

The variance of the normalized error terms is block-orthogonal with block-diagonal entries:

$$\Sigma_{ii} = \left(B_{0,ii}^{-1}\right)\left(B_{0,ii}^{-1}\right)'$$

Replace $F(L) = B_0 - B(L)$ in block equation:

$$\begin{pmatrix} B_{0,11}^{-1} & 0 \\ 0 & B_{0,22}^{-1} \end{pmatrix} \begin{pmatrix} B_{0,11} - B_{11}(L) & B_{0,12} - B_{12}(L) \\ B_{0,21} - B_{21}(L) & B_{0,22} - B_{22}(L) \end{pmatrix} \begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} B_{0,11}^{-1} & 0 \\ 0 & B_{0,22}^{-1} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

Each block (for $i = 1, 2$) then writes as:

$$B_{0,ii}^{-1} \left[\begin{array}{cc} B_{0,ii} - B_{ii}(L) & B_{0,ij} - B_{ij}(L) \end{array}\right] \begin{pmatrix} Y_{it} \\ Y_{jt} \end{pmatrix} = B_{0,ii}^{-1}\varepsilon_{it}$$

$$\left[I - B_{0,ii}^{-1}B_{ii}(L)\right] Y_{it} + \left[B_{0,ii}^{-1}B_{0,ij} - B_{0,ii}^{-1}B_{ij}(L)\right] Y_{jt} = B_{0,ii}^{-1}\varepsilon_{it}$$

If there is block recursion (defined as a lower triangular Cholesky decomposition), i.e. block j (2) does not impact block i (1) contemporaneously, we have $B_{0,ij} = 0$:

$$\left[I - B_{0,ii}^{-1}B_{ii}(L)\right] Y_{it} - B_{0,ii}^{-1}B_{ij}(L)Y_{jt} = B_{0,ii}^{-1}\varepsilon_{it}$$

If, in addition there is block exogeneity, i.e. block j (2) does not impact block i (1) at any horizon, we have $B_{0,ij} = 0$ and $B_{ij}(L) = 0$:

$$\left[I - B_{0,ii}^{-1}B_{ii}(L)\right] Y_{it} = B_{0,ii}^{-1}\varepsilon_{it}$$

If block 2 does not impact block 1 at any horizon ($B_{0,12} = 0$ and $B_{12}(L) = 0$), the two blocks can be estimated separately. Block 1 consists in regressing contemporaneous values of the variables in block 1 on their lagged values:

$$Y_{1t} = B_{0,11}^{-1}B_{11}(L)Y_{1t} + B_{0,11}^{-1}\varepsilon_{1t}$$

Block 2 consists in regressing contemporaneous values of the variables in block 2 lagged values of all variables, but also on contemporaneous values of the variables in block 2:

$$Y_{2t} = B_{0,22}^{-1}B_{22}(L)Y_{2t} + \left[B_{0,22}^{-1}B_{21}(L) - B_{0,22}^{-1}B_{0,21}\right] Y_{1t} + B_{0,22}^{-1}\varepsilon_{2t}$$

Due to the block-recursive structure of the model, there is a one-to-one mapping between $B_{0,ii}$ and Σ_{ii}. We therefore employ a Gibbs sampler to alternately draw Σ_{ii} from an inverted Wishart distribution and the reduced form coefficients from a normal distribution. The structural parameters can be recovered from the reduced form model by the direct mapping via $B_{0,ii}$. In particular, the estimate of the contemporaneous impact matrix, $B_{0,21}$, can be retrieved from its reduced-form estimate $B_{0,22}^{-1}B_{0,21}$, by premultiplication with $B_{0,22}$. As described in appendix B., we also implement an informative prior for the BVAR with block exogeneity. The Minnesota prior moments are chosen similarly to the baseline model.

Since the purpose of imposing block exogeneity is to identify the same technology shock across all models which only differ in the sectoral investment variable that is added to the system, we fix the hyperparameters for block 1 (ϕ_1, $\phi_{4,j}^{(1)}$ and $\psi_i^{(1)}$, where the superscript refers to the variables in block 1) to the estimates from the baseline model and estimate the remaining parameters ($\phi_{4,j}^{(2)}$ and $\psi_i^{(2)}$) via the empirical Bayes method described in appendix B.. Given that ϕ_1, $\phi_{4,j}^{(1)}$ and $\psi_i^{(1)}$ are fixed in this set-up, we maximize the logarithm of the marginal likelihood corresponding to the second block to find the values of $\phi_{4,j}^{(2)}$ and $\psi_i^{(2)}$.

D. Non-fundamentalness in VAR representations

Consider a Wold representation for Y_t:

$$Y_t = K(L)u_t \quad \text{where} \quad E[u_t u_t'] = \Sigma$$

where $K(L)$ is a lag polynomial. This moving average representation is not unique as shown by Hansen and Sargent (1991a). *First*, one can obtain an observationally equivalent representation by finding a matrix which maps the reduced-form errors into structural ones:

$$Y_t = K(L)CC^{-1}u_t = D(L)\varepsilon_t$$

Defining the structural shocks as $\varepsilon_t = C^{-1}u_t$ and the propagation matrix as $D(L) = K(L)C$, the above transformation is concerned with the well-known problem of *identification*. Knowledge or assumptions about the structure of the matrix C, motivated by economic theory, helps recovering the structural shocks. A *second* form of non-uniqueness, non-fundamentalness, is hardly ever discussed in empirical applications of structural vector autoregressions, but is as important as identification. As discussed in Hansen and Sargent (1991a,b), there exist other moving-average representations such as:

$$Y_t = \overline{K}(L)\overline{u}_t \quad \text{where} \quad E[\overline{u}_t \overline{u}_t'] = \overline{\Sigma}$$

Formally speaking, both Wold representations express Y_t as a *linear* combination of past and current shocks (u_t or $\overline{u}_t$ respectively) which is why their first and second moments coincide. $K(L)$ and $\overline{K}(L)$ and the corresponding white noise processes produce the same autocovariance-generating function:

$$\overline{K}(z)\,\overline{\Sigma}\,\overline{K}(z^{-1}) = K(z)\,\Sigma\,D(z^{-1})$$

Though both the Wold representations of Y_t in terms of u_t and $\overline{u}_t$ display the same autocovariance structure, the interpretation of u_t and $\overline{u}_t$ is not the same. In particular, if the space spanned by $\overline{u}_t$ is larger than the one spanned by Y_t, the structural shocks cannot be recovered from *past* and *current* observations of Y_t. In this case, knowing Y_t is not enough to identify ε_t, independently of the identification assumptions in C. We then say that the Wold representation is not fundamental: the polynomial $\overline{K}(L)$ has at least one root inside the unit circle and is thus not invertible.

Alessi *et al.* (2011) summarize and discuss conditions for non-fundamentalness. In an important contribution to this literature, Lippi and Reichlin (1993) show that specific assumptions on the diffusion process, i.e. on the functional form of $\overline{K}(L)$, must be made in order to ensure that the identifed process is fundamental. In the specific case of Lippi and Reichlin (1993), non-fundamentalness arises as learning-by-doing dynamics lead to a delayed increase in productivity following a technology shock.

Recently, the news shock literature has reconsidered the issue of non-fundamentalness. Shocks are pre-announced, be it due to fiscal foresight (Leeper *et al.*, 2011) or due to news about future productivity (Fève *et al.*, 2009; Leeper and Walker, 2011). Whenever the pre-announcement of shocks is observed by economic agents but not by the econometrician, VAR representations can be plagued by non-fundamentalness: future observations Y_{t+q} (with q corresponding to the announcement lag) must be included into the model in order to recover the fundamental shock in t.

E. Data sources

Variable	Description	Source	Details
Standards	Number of standards released by American standard setting organizations	PERINORM database	
Output	Output in business sector (BLS ID: PRS84006043)	Bureau of Labor Statistics (BLS)	Index (2009=100), seasonal and per capita adjustment
Investment	Real private fixed investment (NIPA table 5.3.3 line 1)	Bureau of Economic Analysis (BEA)	Index (2009=100), seasonal and per capita adjustment
	Equipment (NIPA table 5.3.3 line 9)		
	Information processing equipment (NIPA table 5.3.3 line 10)		
	Computers and peripheral equipment (NIPA table 5.3.3 line 11)		
	Other equipment (NIPA table 5.3.3 line 12)		
	Industrial equipment (NIPA table 5.3.3 line 13)		
	Transportation equipment (NIPA table 5.3.3 line 14)		
	Other equipment (NIPA table 5.3.3 line 15)		
	Intellectual property products (NIPA table 5.3.3 line 16)		
	Software (NIPA table 5.3.3 line 17)		
	Research and development (NIPA table 5.3.3 line 18)		
	Entertainment, literary, and artistic originals (NIPA table 5.3.3 line 19)		
Consumption (Real personal consumption)	Consumption expenditures for goods and services (NIPA table 2.3.3 line 1)	Bureau of Economic Analysis (BEA)	Index (2009=100), seasonal and per capita adjustment
Hours	Hours worked in business sector (BLS ID: PRS84006033)	Bureau of Labor Statistics (BLS)	Index (2009=100), seasonal and per capita adjustment
Total factor productivity	Capacity utilization adjusted total factor productivity (based on data from business sector)	John Fernald (San Francisco Fed)	Index (1947 = 100)
	Capacity utilization adjusted total factor productivity in "investment sector" (equipment and consumer durables)		
	Capacity utilization adjusted total factor productivity in "consumption sector" (non-equipment)		
Stock market indices	S&P 500	Datastream	Deflated, per capita adjustment
	NASDAQ Composite Index		
Capacity utilization	Capacity utilization, total index	Federal Reserve Board	Index in %, seasonal adjustment
Relative price of investment	Price of investment in equipment (NIPA table 5.3.4 line 9) divided by the price index for personal consumption expenditures for non-durable goods (NIPA table 2.3.4 line 8)	Bureau of Economic Analysis (BEA)	Indices (2009=100), seasonal adjustment
Federal funds rate	Federal fund effective rate	Federal Reserve Board	In %
Population	Civilian noninstitutional population over 16 (BLS ID: LNU00000000Q)	Bureau of Labor Statistics (BLS)	In hundreds of millions
Price deflator	Implicit price deflator of GDP in the business sector (BLS ID: PRS84006143)	Bureau of Labor Statistics (BLS)	Index (2009=100), seasonal adjustment

F. Construction of standards data

We obtain information on standard releases from the PERINORM database. PERINORM is a standards library hosted by the national standards setting organizations of France, Germany and the UK. Those national standard organizations also collect and publish information on standards issued by a large number of other organizations, including 20 of the most relevant standard setting organizations in the US. To the best of our knowledge, PERINORM is the most comprehensive available database on standard documents. It comprises detailed bibliographic information on more than 1,500,000 standard documents. We retrieved in October 2013 the information on all standard documents issued by an American (135,340 documents) or international SSO (156,255 documents). The first standard release in our database dates back to 1906. For each standard, we retrieve (when available) the identity of the issuing SSO, the date of standard release, references to other standards, equivalence with other standards, version history (information on preceding or succeeding versions), number of pages and the technological classification.

In a first step, we restrict the sample to standards applying to the US. We thus use all standard documents issued by an organization with the country code "US". This results in a list of 20 organizations. These 20 organizations are only a subset of the hundreds of standards consortia active in the US, but our sample includes the most established formal SSOs. The largest SSOs in the sample are the American Society for Testing and Materials (59,622 standard documents), the American National Standards Institute (35,704 standards documents), and the Society for Automotive Engineers (21,022 standards documents). The sample consists in both standards that are originally produced by these organizations, and in standards produced by other organizations, but receiving official accreditation from one of these organizations. Several standards receive accreditation from more than one organization in our sample. We use information on the equivalence between standard documents to remove duplicates (always keeping the earliest accreditation of a standard in the sample).

Many important international standards enter our sample when they receive accreditation by an American SSO. Other international standards can however also be relevant to the US economy. We therefore carry out a second analysis covering also standard documents issued by international organizations (such as ISO). Once again, we remove duplicates using information on standard equivalence. Including standards from the international standards bodies allows for instance covering the 3G and 4G mobile telecommunication standards applying in the US. These standards were set in a worldwide effort in the Third Generation Partnership Project (3GPP). The US 3GPP member organization ATIS is not part of our sample, but we can use the equivalent standards from ETSI, another 3GPP member. The World Administrative Telegraph and Telephone Conference (WATTC) which took place in Melbourne in 1988 was decisive for the International Telecommunication Regulations (ITRs), but also led to the inclusion of several already existing national standards in the ITU standard catalogue. We therefore exclude standards that were released by ITU in the forth quarter of 1988 and that were released under the standards classes 33.02 (Telecommunications in general) and 33.04 (Telecommunication systems).

In a second step, we restrict the sample by technological field. We rely upon the International Classification of Standards (ICS)[22]. We concentrate on the field of Information and Communication Technologies (ICT), which we define as standard documents in the ICS classes 33 ("Telecommunication, Audio and Video Engineering") and 35 ("Information Technology, Office Machines"). Standards in these ICS classes are the most closely related to technological innovation.[23] We also perform analyses on a wider definition of ICT, including ICS classes 31 ("Electronics") and 37 ("Image Technology").

We count the number of standard documents released by quarter. In several cases, the PERINORM database only includes information on the year, but not the month or day of standard release. For a significant number of standards, we were able to retrieve this information manually from a different source (http://www.document-center.com). For the series containing standards from US SSOs only ("US"), we have information on both the quarter and the year of release for 67% of the standards in the period 1975Q1–2011Q4. For the series which contains both standards from US and international SSOs only ("US+Int"), this information is available for 94% of all standards. For the remainder of the standards, only the year of release is known to us. In order to adjust our final series, we distribute the remaining documents uniformly over the quarters of the year in question.

Standards differ significantly in their economic and technological importance. In order to account for this heterogeneity, we execute different weighting methods. *First*, we weight standard documents by the number of pages. SSOs have a strong incentive to keep standard documents short. Every technological description in a standards document binds the firms implementing the standard in their products and processes. The number of pages of the standard document is thus an acceptable indicator of the amount of technological content. *Second*, we weigh the number of documents by the number of times a standard is referenced by ulterior standard documents. A standard references another standard if the implementation of the referencing standard makes the implementation of the referenced standard necessary. The implementation of the referenced standard is part of the standardized procedure described in the referencing standard. The number of references from ulterior standard documents is thus a good indicator for the extent to which a standard is used in different applications. In order to compare the relevance of standards released at different points in time, we only count the references received within the first four years after the standard release (and accordingly we are only able to use standard documents released up to 2009 for this analysis). We choose a window of four years, because the yearly rate of incoming references is highest in the first four years after the release. About one half of all the standard references are made within the first four years after release.

In a last step, we distinguish between new and upgraded standards. A standard upgrade is a new version replacing an older version of the same standard. We assume that standard upgrades are minor, more continuous improvements compared to the more fundamental, discontinuous technological progress embodied in a completely new standard. We thus identify and separate from the sample all standard documents which replace a preceding standard version.

[22]For more details, see the below table A1 and http://www.iso.org/iso/ics6-en.pdf.

[23]For instance, standards in these classes account for 98% of all declared standard-essential patents (Baron *et al.*, 2013).

Table A1: International classification of standards (ICS)

ICS class	Description
1	Generalities. Terminology. Standardization. Documentation.
3	Services. Company organization, management and quality. Administration. Transport. Sociology.
7	Mathematics. Natural sciences.
11	Health care technology.
13	Environment. Health protection. Safety.
17	Metrology and measurement. Physical phenomena.
19	Testing.
21	Mechanical systems and components for general use.
23	Fluid systems and components for general use.
25	Manufacturing engineering.
27	Energy and heat transfer engineering.
29	Electrical engineering.
31	Electronics.
33	Telecommunications. Audio and video engineering.
35	Information technology. Office machines.
37	Image technology.
39	Precision mechanics. Jewelry.
43	Road vehicles engineering.
45	Railway engineering.
47	Shipbuilding and marine structures.
49	Aircraft and space vehicle engineering.
53	Materials handling equipment.
55	Packaging and distribution of goods.
59	Textile and leather technology.
61	Clothing industry.
65	Agriculture.
67	Food technology.
71	Chemical technology.
73	Mining and minerals.
75	Petroleum and related technologies.
77	Metallurgy.
79	Wood technology.
81	Glass and ceramics industries.
83	Rubber and plastic industries.
85	Paper technology.
87	Paint and colour industries.
91	Construction materials and building.
93	Civil engineering.
95	Military engineering.
97	Domestic and commercial equipment. Entertainment. Sports.
99	(No title)

Source: International Organization for Standards (2005)

References

Acemoglu, Daron, Gino Gancia and Fabrizio Zilibotti (2012): Competing Engines of Growth: Innovation and Standardization. *Journal of Economic Theory*, 147(2), pp. 570–601.

Aghion, Philippe, Philippe Askenazy, Nicolas Berman, Gilbert Cette and Laurent Eymard (2012): Credit Constraints and the Cyclicality of R&D Investment: Evidence from France. *Journal of the European Economic Association*, 10(5), pp. 1001–1024.

Alessi, Lucia, Matteo Barigozzi and Marco Capasso (2011): Non-Fundamentalness in Structural Econometric Models: A Review. *International Statistical Review*, 79(1), pp. 16–47.

Alexopoulos, Michelle (2011): Read All about It!! What Happens Following a Technology Shock? *American Economic Review*, 101(4), pp. 1144–1179.

Altig, David, Lawrence Christiano, Martin Eichenbaum and Jesper Lindé (2005): Technical Appendix to "Firm-Specific Capital, Nominal Rigidities and the Business Cycle". Technical Appendices No. 09-191, Review of Economic Dynamics.

Andolfatto, David and Glenn MacDonald (1998): Technology Diffusion and Aggregate Dynamics. *Review of Economic Dynamics*, 1(2), pp. 338–370.

Barlevy, Gadi (2007): On the Cyclicality of Research and Development. *American Economic Review*, 97(4), pp. 1131–1164.

Baron, Justus, Tim Pohlmann and Knut Blind (2013): Essential Patents and Standard Dynamics. Mimeo.

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

Basu, Parantap and Christoph Thoenissen (2011): International Business Cycles and the Relative Price of Investment Goods. *Canadian Journal of Economics*, 44(4), pp. 580–606.

Basu, Susanto and John G. Fernald (2008): Information and Communications Technology as a General Purpose Technology: Evidence from U.S. Industry Data. *Federal Reserve Bank of San Francisco Economic Review*, pp. 1–15.

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

Beaudry, Paul and Franck Portier (2006): Stock Prices, News, and Economic Fluctuations. *American Economic Review*, 96(4), pp. 1293–1307.

Bekkers, Rudi and Joel West (2009): The limits to IPR standardization policies as evidenced by strategic patenting in UMTS. *Telecommunications Policy*, 33(1-2), pp. 80–97.

Canova, Fabio (2007): *Methods for Applied Macroeconomic Research.* Princeton University Press.

Canova, Fabio, David Lopez-Salido and Claudio Michelacci (2010): The Effects of Technology Shocks on Hours and Output: A Robustness Analysis. *Journal of Applied Econometrics*, 25(5), pp. 755–773.

Carriero, Andrea, Todd Clark and Massimiliano Marcellino (2011): Bayesian VARs: specification choices and forecast accuracy. Tech. rep.

Chari, V.V., Patrick J. Kehoe and Ellen R. McGrattan (2008): Are Structural VARs with Long-Run Restrictions Useful in Developing Business Cycle Theory? *Journal of Monetary Economics*, 55(8), pp. 1337–1352.

Cochrane, John H. (1994): Shocks. *Carnegie-Rochester Conference Series on Public Policy*, 41(1), pp. 295–364.

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

Comin, Diego and Bart Hobijn (2010): An Exploration of Technology Diffusion. *American Economic Review*, 100(5), pp. 2031–2059.

Comin, Diego A., Mark Gertler and Ana Maria Santacreu (2009): Technology Innovation and Diffusion as Sources of Output and Asset Price Fluctuations. NBER Working Paper No. 15029, National Bureau of Economic Research.

Cooley, Thomas F., Jeremy Greenwood and Mehmet Yorukoglu (1997): The Replacement Problem. *Journal of Monetary Economics*, 40(3), pp. 457–499.

DiCecio, Riccardo and Michael T. Owyang (2010): Identifying Technology Shocks in the Frequency Domain. Working Paper No. 25, Federal Reserve Bank of St. Louis.

Farrell, Joseph and Garth Saloner (1985): Standardization, Compatibility, and Innovation. *RAND Journal of Economics*, 16(1), pp. 70–83.

Farrell, Joseph and Garth Saloner (1986): Installed Base and Compatibility: Innovation, Product Preannouncements, and Predation. *American Economic Review*, 76(5), pp. 940–955.

Fisher, Jonas D. M. (2006): The Dynamic Effects of Neutral and Investment-Specific Technology Shocks. *Journal of Political Economy*, 114(3), pp. 413–451.

Fontana, Roberto, Alessandro Nuvolari and Bart Verspagen (2009): Mapping Technological Trajectories as Patent Citation Networks. An Application to Data Communication Standards. *Economics of Innovation and New Technology*, 18(4), pp. 311–336.

Francois, Patrick and Huw Lloyd-Ellis (2003): Animal Spirits Through Creative Destruction. *American Economic Review*, 93(3), pp. 530–550.

Fève, Patrick and Ahmat Jidoud (2012): Identifying News Shocks from SVARs. TSE Working Paper No. 12-287, Toulouse School of Economics (TSE).

Fève, Patrick, Julien Matheron and Jean-Guillaume Sahuc (2009): On the Dynamic Implications of News Shocks. *Economics Letters*, 102(2), pp. 96–98.

Galí, Jordi (1999): Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations? *American Economic Review*, 89(1), pp. 249–271.

Gandal, Neil, Nataly Gantman and David Genesove (2004): Intellectual Property and Standardization Committee Participation in the US Modem Industry. CEPR Discussion Paper No. 4658, Centre for Economic Policy Research.

Geroski, Paul A. and Chris F. Walters (1995): Innovative Activity over the Business Cycle. *Economic Journal*, 105(431), pp. 916–928.

Giannone, Domenico, Michele Lenza and Lucrezia Reichlin (2012a): Money, Credit, Monetary Policy and the Business Cycle in the Euro Area. ECARES Working Paper No. 8, ULB - Université Libre de Bruxelles.

Giannone, Domenico, Michèle Lenza and Giorgio E. Primiceri (2012b): Prior Selection for Vector Autoregressions. Mimeo.

Greenwood, Jeremy, Zvi Hercowitz and Gregory W. Huffman (1988): Investment, Capacity Utilization, and the Real Business Cycle. *American Economic Review*, 78(3), pp. 402–417.

Greenwood, Jeremy, Zvi Hercowitz and Per Krusell (1997): Long-Run Implications of Investment-Specific Technological Change. *American Economic Review*, 87(3), pp. 342–362.

Greenwood, Jeremy, Zvi Hercowitz and Per Krusell (2000): The Role of Investment-Specific Technological Change in the Business Cycle. *European Economic Review*, 44(1), pp. 91–115.

Greenwood, Jeremy and Mehmet Yorukoglu (1997): 1974. *Carnegie-Rochester Conference Series on Public Policy*, 46(1), pp. 49–95.

Griliches, Zvi (1957): Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica*, 25(4), pp. 501–522.

Griliches, Zvi (1990): Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4), pp. 1661–1707.

Hairault, Jean-Olivier, cois Langot, Fran and Franck Portier (1997): Time to implement and aggregate fluctuations. *Journal of Economic Dynamics and Control*, 22(1), pp. 109–121.

Hansen, Lars Peter and Thomas J. Sargent (1991a): Introduction. In: Lars Peter Hansen and Thomas J. Sargent (eds.), *Rational Expectations Econometrics*, pp. 1–12. Westview Press, Boulder.

Hansen, Lars Peter and Thomas J. Sargent (1991b): Two Difficulties in Interpreting Vector Autoregressions. In: Lars Peter Hansen and Thomas J. Sargent (eds.), *Rational Expectations Econometrics*, pp. 77–119. Westview Press, Boulder.

Helpman, Elhanan and Manuel Trajtenberg (1996): Diffusion of General Purpose Technologies. NBER Working Paper No. 5773, National Bureau of Economic Research.

Hillebrand, Friedhelm, Karl-Heinz Rosenbrock and Hans Hauser (2013): The Creation of Standard for Global Mobile Communication: GSM, UMTS and LTE from 1982 to 2012. E-Book available at:http://www.etsi.org/index.php/news-events/news/710-2013-11-new-ebook-published-and-made-available.

Hobijn, Bart and Boyan Jovanovic (2001): The Information-Technology Revolution and the Stock Market: Evidence. *American Economic Review*, 91(5), pp. 1203–1220.

Hornstein, Andreas and Per Krusell (1996): Can Technology Improvements Cause Productivity Slowdowns? In: *NBER Macroeconomics Annual 1996, Volume 11*, NBER Chapters, pp. 209–276. National Bureau of Economic Research.

International Organization for Standards (2005): *International Classification for Standards*. Geneva, 6th ed.

Jaimovich, Nir and Sergio Rebelo (2009): Can News about the Future Drive the Business Cycle? *American Economic Review*, 99(4), pp. 1097–1118.

Jovanovic, Boyan (1995): Learning and Growth. NBER Working Paper No. 5383, National Bureau of Economic Research.

Jovanovic, Boyan and Saul Lach (1989): Entry, Exit, and Diffusion with Learning by Doing. *American Economic Review*, 79(4), pp. 690–699.

Justiniano, Alejandro, Giorgio Primiceri and Andrea Tambalotti (2011): Investment Shocks and the Relative Price of Investment. *Review of Economic Dynamics*, 14(1), pp. 101–121.

Justiniano, Alejandro, Giorgio E. Primiceri and Andrea Tambalotti (2010): Investment Shocks and Business Cycles. *Journal of Monetary Economics*, 57(2), pp. 132–145.

Kadiyala, K Rao and Sune Karlsson (1997): Numerical Methods for Estimation and Inference in Bayesian VAR-Models. *Journal of Applied Econometrics*, 12(2), pp. 99–132.

Katz, Michael L. and Carl Shapiro (1985): Network Externalities, Competition, and Compatibility. *American Economic Review*, 75(3), pp. 424–440.

King, Robert G., Charles I. Plosser, James H. Stock and Mark W. Watson (1991): Stochastic Trends and Economic Fluctuations. *American Economic Review*, 81(4), pp. 819–840.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru and Noah Stoffman (2012): Technological Innovation, Resource Allocation, and Growth. NBER Working Paper No. 17769, National Bureau of Economic Research.

Leeper, Eric and Todd Walker (2011): Information Flows and News Driven Business Cycles. *Review of Economic Dynamics*, 14(1), pp. 55–71.

Leeper, Eric M., Todd B. Walker and Shu-Chun Susan Yang (2011): Foresight and Information Flows. Mimeo.

Lippi, Marco and Lucrezia Reichlin (1993): The Dynamic Effects of Aggregate Demand and Supply Disturbances: Comment. *American Economic Review*, 83(3), pp. 644–652.

Lippi, Marco and Lucrezia Reichlin (1994): Diffusion of Technical Change and the Decomposition of Output into Trend and Cycle. *Review of Economic Studies*, 61(1), pp. 19–30.

Ouyang, Min (2011): On the Cyclicality of R&D. *The Review of Economics and Statistics*, 93(2), pp. 542–553.

Pástor, Lubos and Pietro Veronesi (2009): Technological Revolutions and Stock Prices. *American Economic Review*, 99(4), pp. 1451–1483.

Ravenna, Federico (2007): Vector Autoregressions and Reduced Form Representations of DSGE Models. *Journal of Monetary Economics*, 54(7), pp. 2048–2064.

Rysman, Marc and Timothy Simcoe (2008): Patents and the Performance of Voluntary Standard-Setting Organizations. *Management Science*, 54(11), pp. 1920–1934.

Samaniego, Roberto M. (2006): Organizational Capital, Technology Adoption and the Productivity Slowdown. *Journal of Monetary Economics*, 53(7), pp. 1555–1569.

Schmitt-Grohé, Stephanie and Martin Uribe (2012): What's News in Business Cycles. *Econometrica*, 80(6), pp. 2733–2764.

Shea, John (1999): What Do Technology Shocks Do? In: *NBER Macroeconomics Annual 1998, volume 13*, NBER Chapters, pp. 275–322. National Bureau of Economic Research.

Shleifer, Andrei (1986): Implementation Cycles. *Journal of Political Economy*, 94(6), pp. 1163–1190.

Sims, Christopher A and Tao Zha (1998): Bayesian Methods for Dynamic Multivariate Models. *International Economic Review*, 39(4), pp. 949–968.

Sims, Eric R. (2012): News, Non-Invertibility, and Structural VARs. *Advances in Econometrics*, 28, pp. 81–136.

Smets, Frank and Rafael Wouters (2007): Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic Review*, 97(3), pp. 586–606.

Trajtenberg, Manuel (1990): A Penny for Your Quotes: Patent Citations and the Value of Innovations. *RAND Journal of Economics*, 21(1), pp. 172–187.

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

Waggoner, Daniel F. and Tao Zha (2003): A Gibbs sampler for structural vector autoregressions. *Journal of Economic Dynamics and Control*, 28(2), pp. 349–366.

Yorukoglu, Mehmet (1998): The Information Technology Productivity Paradox. *Review of Economic Dynamics*, 1(2), pp. 551–592.

Zha, Tao (1999): Block recursion and structural vector autoregressions. *Journal of Econometrics*, 90(2), pp. 291–316.

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