Technological Standardization, Endogenous Productivity and Transitory Dynamics

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Abstract

This paper examines empirically the transitory dynamics of macroeconomic variables in response to technology shocks for which we propose a novel indicator. In particular, we use standards as a measure of adoption of new or drastically improved technologies. Standardization is an important feature of technological progress in many industries. As such, standards represent the clustered adoption of bundles of inventions and set the technological basis for further innovative activity. *First*, we find that standardization is an important driver for investment and long-run productivity thus confirming our interpretation of standardization as an indicator of technological progress. However, following a standardization shock, aggregate productivity temporarily decreases before picking up permanently. Disembodied productivity can temporarily slow down whenever a newly adopted technology is incompatible with installed physical, human and organizational capital. *Second*, our results suggest that both inventive activity, as measured by patenting, and the actual adoption of new technologies, as measured by standards, are endogenous to the cycle. This finding implies that technology is not a purely exogenous phenomenon whose circular feedback with the macroeconomic cycle can simply be ignored. *Third*, this paper finds that standardization is an essential mechanism for anchoring technological expectations as evidenced by the positive reaction of stock market data to a standardization shock. It is shown that this reduction of uncertainty plays an important role for incentivizing further incremental innovation.

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1 Introduction

Despite a very long and on-going debate, technology remains a popular explanation for business cycle fluctuations. However, the perception of technology in a macroeconomic context is still a vague concept which differs from the more literal interpretation of technology as it is understood outside of macroeconomics.

This paper seeks to validate empirically the impact of technology on productivity and to gain more insight into the feedback mechanism between innovation and the macroeconomic cycle. Using extensive technological data and new micro-founded indicators of technological change (in particular technological standards), we study the effect of technology shocks on macroeconomic aggregates - a question which still figures on the research agenda of macroeconomists due to the difficulty of identifying technology shocks. Standards precede the coordinated adoption of new technologies and anchor the expectations about future technological progress by reducing uncertainty and ensuring technological homogeneity. Using a direct, micro-level indicator of technological progress allows us to look into the specific channels that lead to technological change. We therefore not only look at the impact of technology on productivity and the cycle, but also analyze inasmuch technology is cycle-driven.

The seminal papers of Kydland and Prescott (1982) and Long and Plosser (1983) developed the concept of stochastic technological change as an exogenous driver of business cycles. Despite the critique of the Real Business Cycle (RBC) hypothesis, the idea of technology being a decisive factor for business cycle fluctuations has not lost its attractiveness. More recently, models have increasingly relied on shocks to the marginal efficiency of investment as defined by Greenwood *et al.* (1988). These investment-specific technology (IST) shocks are more often directly associated with technological change taken literally as they only affect *new* vintages of capital.[1] It thus requires investment in new machinery and human capital to realize technical progress. The concept of "vintage capital" is used in particular for models which stress that technological change is only *embodied* in new vintages of capital and thus leads to technological obsolescence and economic depreciation (as opposed to physical depreciation).[2] The approach taken in this paper follows this notion of technology.[3]

Though technology is an important concept in macroeconomics, business cycle economists - in contrast to endogenous growth theories - have made less use of the insights from the

[1] Greenwood *et al.* (1997) show that 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.

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

[3] Using industry-level data, Boddy and Gort (1974) do indeed show that productivity changes can for the most part be traced back to changes in embodied technology. A similar point is made by Greenwood *et al.* (1997, 2000) who show that more than 60% of long-term productivity growth and 30% of short-term fluctuations are driven by investment-specific technological change. Fisher (2006) analyzes theoretically and empirically the quantitative effects of neutral and investment-specific technology shocks on business cycle fluctuations. He finds that the latter is the larger driver of volatility.

industrial organization literature on microeconomic mechanisms relating to technology adoption. However, a thorough understanding of the role of technology is necessary given that a large strand of the business cycle literature still relies heavily upon exogenous technology shocks as a driver of short-run fluctuations.

The recent literature on "news shocks" (Beaudry and Portier, 2006) has contributed to the revival of the idea that technology, or in this case news about future technological improvements, drives business cycles. Anticipated improvements in total factor productivity lead to business cycle fluctuations despite the fact that the shock only materializes after several lags. Technological progress which is characterized by long diffusion lags is similar to such dynamics. The implications of technological diffusion pose macroeconometric challenges which require the use of meaningful information (Lippi and Reichlin, 1993; Leeper *et al.*, 2011). The identification of technology shocks, however, has proven challenging territory and a large and lively debated literature on the correct identification of technology shocks has been keeping macroeconomists busy.

In this paper, we propose to use data on standardization to capture technological diffusion. Technological standards are comparable to patents in that they are documents which describe the technical features of innovations and technologies. However, in contrast to patents which have been shown to be poor indicators of technological change, standards are economically and technologically highly meaningful, reflect the actual adoption (instead of invention) of an innovation and *trigger* technological diffusion.

Our indicator allows us to address various questions. As such, we analyze the effect of technology on productivity and its implications for business cycle fluctuations. Since standards are a direct measure of adoption activity, explicit mechanisms and channels of technology adoption can be addressed. We not only investigate inasmuch technological change affects the macroeconomic aggregates, but also ask which factors actually lead to technology adoption and which specific patterns of technological innovation and adoption characterize the dynamics of technological change. We therefore attempt to explain technology as a phenomenon itself instead of considering technology as a simple exogenous force. Figure 1 illustrates the conceptual framework in which our analysis of technology is embedded.

Our findings can be be grouped into three major points. *First*, we find that standardization is an important driver for investment in equipment and software as well as for long-run productivity thus confirming our interpretation of standardization as an indicator of technological progress. Most interestingly, we find that aggregate disembodied productivity decreases following a shock to embodied technology due to the incompatibility of new and old vintages of capital. *Second*, we investigate if technology is indeed exogenous as often assumed in macroeconomics. We find that technology adoption is actually cycle-driven and relate this finding to the importance of economic incentives (demand effects) and liquidity constraints in the light of high adoption costs. *Third*, the results suggest that standardization is an essential mechanism for anchoring technological expectations and communicating "news" to economic agents about future productivity in the spirit of Beaudry and Portier (2006). We find that the reduction of uncertainty due to standardization is an important device to endogenize future innovation.

The next section motivates and discusses the relevance of our new measure of technological change and reviews the literature. Section 3 describes the data and methodology. Section 4 presents the results and their interpretation. Section 5 concludes.

2 Challenges for indicators of technological progress

2.1 Technological diffusion, fundamentalness and information

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

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

Defining the structural shocks as $\varepsilon_t = C^{-1}u_t$ and the propagation matrix as $\tilde{D}(L) = D(L)C$, the above transformation is concerned with the well-known problem of *identification*. Knowledge or assumptions about the structure of the matrix C, preferably motivated by economic theory, helps recovering the structural shocks. A second form of non-uniqueness is hardly ever discussed in empirical applications of structural vector autoregressions, but is as important as identification. The problem arises whenever the *information* spanned by the structural shocks is larger than the space covered by Y_t. In this case, knowing Y_t is not enough to recover ε_t.

Formally speaking, a VAR representation is fundamental if its structural shocks can be recovered from *past* and *current* observations of Y_t. This is the case when the moving-average representation is invertible.[4] Lippi and Reichlin (1993, 1994) show that S-shaped diffusion curves, as they are typical for patterns of technology adoption, can lead to non-fundamental representations unless the diffusion process is assumed to have a certain functional form.[5] Potentially, the econometrician identifies shocks which are actually moving averages of the fundamental innovations.

In a nutshell, there are two ways to solve the non-fundamentalness problem. The first one consists in modelling information flows directly which entails making very strong assumptions about time lags and functional forms of diffusion processes or the way news

[4] Invertibility of $\tilde{D}(L)$ is given when the roots of the determinant of the polynomial $\tilde{D}(L)$ are greater than one in modulus.

[5] Non-fundamentalness can as well arise in other contexts that are similar to technological diffusions. The macroeconometric literature has also considered models with foresight (Leeper *et al.*, 2011) and news shocks (Fève *et al.*, 2009; Fève and Jidoud, 2012; Leeper and Walker, 2011). News shocks in particular are often associated with technological progress.

shock materialize. The second one is about using direct measures of news or diffusion which is the approach taken in this paper. Essentially, we try to align the *information set* of the econometrician with the one of the agents.

2.2 Indicators of technological progress

The empirical identification of technology shocks thus constitutes a, if not *the*, major challenge in the RBC literature.[6] The macroeconomic literature on technology shocks has mainly worked with long-run restrictions to identify productivity shocks following the seminal work of Galí (1999). Identification is indirect by postulating how technology shocks should behave in the long-run and by assuming that the common stochastic trend found in macroeconomic variables represents exclusively permanent technology shocks (King *et al.*, 1991). The analysis of short-run effects is however flawed if the assumption is violated and technology is not the only variable affecting productivity in the long-run.

Another means of identifying technological change from macroeconomic data is to use corrected measures of Solow residuals by adjusting raw measures of total factor productivity (TFP) for capacity utilization, increasing returns, imperfect competition and aggregation effects (Basu *et al.*, 2006). The latter approach, however, suffers from the assumption that once residuals are adjusted for non-technological factors, the remaining technology component is considered purely exogenous. As will be shown later, cycle-driven technology adoption seriously challenges this conjecture.

To address the problem that long-run restrictions might capture not only technology, but also non-technological factors, more direct measures of technological change can be used. All these indicators have in common that they consider technological change to be embodied. One the one hand, a vast literature relies on R&D and patent data to capture direct indicators of technological change (Shea, 1998; Kogan *et al.*, 2012). On the other hand, proxies for the adoption of technological innovations have been used: Alexopoulos (2011) relies on technology publications such as manuals as a measure for technology adoption and Serrano (2007) uses data on the transfer of the ownership of patents to obtain an indicator of technological change.

The measures described above display several advantageous features, but are also plagued by some shortcomings. Patent counts and data on R&D expenditures represent innovative activity and therefore directly measure technological change. However, R&D expenditure and patent counts often tell little about the economic significance of an innovation and are only indirectly related to the introduction of new technologies. R&D

[6]The correct identification of technology shocks is of such relevance since macroeconomists have been trying to identify the effect of technology shocks on the economy as a whole and in particular on factor inputs. Even if technology shocks have only a small impact on the cycle, the question remains nevertheless an important one: whether factor inputs react positively or contract is respectively interpreted as a proof for the RBC paradigm or as an indication for the validity of sticky-price models of the New-Keynesian type.

expenditures measure the input, but not the output of inventive activity, and patent counts measure inventions and not the actual implementation of a new technology.

Indicators such as technology publications and patent reassignments are indicators which measure exclusively innovations that are actually commercialized and thus capture economically significant innovations. More importantly, the measures used by Alexopoulos (2011) and Serrano (2007) are temporally close to the actual date of adoption of a new technology. Nevertheless, these indicators measure phenomena that are related to technology adoption, but not technology adoption or technological progress itself. This might impede a thorough understanding of the mechanisms and dynamics of technological progress.

Our indicator of technological progress shares the merits of the above technology indicators, but surmounts their shortcomings. Standards are explicit measures of innovative activity and are directly linked to technology adoption. Standardization data allow for the analysis of rich dynamics and mechanisms leading to the implementation of new technologies. Due to the high economic and technical content of standards, we are able to investigate the effects of technology on aggregate macroeconomic variables. Standardization is directly connected to innovative activity on the micro-level and has the advantage of being a driver of the actual implementation of new technologies. In particular, we use data from the information and communications technology (ICT) sector as this industry has been found to be the main driver of productivity growth in recent decades due to its nature as a general purpose technology (GPT) as shown by Basu and Fernald (2008).

2.3 A new measure of technological progress: standardization

Definition and practicalities of standardization

Standards play an important role in the everyday life of all industrialized societies. Prominent examples of standards are electricity plugs, paper size formats (i.e. A4 for most of the world and "letter" size in the US) or quality standards (i.e. ISO 9001:2008). A (technological) standard is essentially a document which pins down *how to do* certain things. A standard describes the required technical features of products and processes and is issued by standard setting organizations on the national and international level. Loosely speaking, our series on standardization is comparable to patent data, but richer in terms of economic content and meaningful for technological implementation. One can distinguish between compatibility standards, variety-reducing standards as well as quality and safety standards.

Standards are set in a number of different ways.[7] De facto standards are set by a market selection process where consumers prefer a certain technology over another, acquire it either by traditional use or due to the monopolistic supply of a unique technology. Especially

[7] See David and Greenstein (1990) for an overview of the different mechanisms that lead to the creation of a standard as well as the discussion in Gandal (2002).

in the latter case these standards are often proprietary. Examples of de facto standards are the QWERTY keyboard or Microsoft's Excel. Voluntary or informal standards are often set by industry organizations and comprise open standards which are mainly non-proprietary. An example is the standard setting activity of the Internet Engineering Task Force (IETF). Formal standards are imposed by national or international standard setting organizations and are binding regulations. Examples of standard setting organizations are the American National Standards Institute (ANSI), the European Telecommunications Standards Institute (ETSI) or the International Organization for Standardization (ISO).

Standard development usually begins with the perception by industry stakeholders that a certain standard is needed in order to ensure compatibility. Working groups within the standard setting organization are created which define the technical scope of the standard to be developed. These working groups are composed of technical experts as well as developers and suppliers. Participation is voluntary, but the outcomes of these intra-industry negotiations are often binding. Farrell and Saloner (1988) show that coordination in standardization committees performs better than pure market selection. It is for this reason that standardization mandated by policy makers might lead to better outcomes for consumers when strong network effects are present (Farrell and Shapiro, 1992).

Most standards are released in the fields of engineering technologies, information and telecommunications as well as materials technologies. Popular examples are the first generation (1G), second generation (2G) and third generation (3G) standards in the mobile phone industry. 1G technology describes a family of standards which defined analog mobile telecommunication systems as they were introduced in the early 1980's. The 2G family of mobile telecommunication standards replaced 1G technology by using digital signals and was introduced in the early 1990's. 3G technology allowed for high-speed data transmission and mobile Internet access and was effectively launched in the early 2000's.[8] In the following, we will discuss the advantages of using standardization data as an indicator of technology diffusion using the specific example of different standard generations for the mobile telecommunications technology. The sequential process of technological change, of which standardization is an essential element, and the interaction of this process with the cycle is displayed in figure 1.

Economic implications of standardization

Compatibility and network effects. The adoption of many new technologies is subject to network effects; standardization is often essential to benefit from these positive externalities (Katz and Shapiro, 1985). Due to technological complexity and the desire to achieve industry-wide compatibility, the participants of a specific industry often choose to adopt new technologies in a coordinated manner through standardization. A relatively large literature in innovation economics addresses the importance of compatibility (standardization) for

[8] See Gandal *et al.* (2003) for a discussion of standard setting practices in Europe and North America for the mobile telecommunications sector.

the adoption of technologies by producers and consumers (Katz and Shapiro, 1985, 1986; David and Greenstein, 1990; Farrell and Saloner, 1988). For our example of mobile telecommunications, standardization assures broad coverage and interconnectivity across different operators. Compatibility is a key issue for most technological applications such as ICT where the benefit from using a technology depends positively on the number of users. The lack of compatibility between different analog 1G telecommunication systems motivated the European Commission to mandate a harmonized standard for 2G technologies in all member countries in order to facilitate roaming.

Standardization as a selection mechanism. A standard chooses one practice among several co-existing practices as the one that is to be applied by a whole industry and therefore lays the ground for the harmonization and compatibility of products and processes. Standardization is a selection mechanism, where one technological option is chosen *as standard* among various alternatives, whereas the competing technologies are discarded. Rysman and Simcoe (2008) show that standardization is an important mechanism for an industry to *identify* relevant technologies and *promote* their use. To take again the example of mobile phone standards, European legislators opted for the UMTS standard family among two competing technologies in order to push the development of 3G technologies.

Reduction of uncertainty and expectations. Via this selection mechanism, standards can therefore reduce uncertainty substantially and define in which direction an industry is heading. Fontana *et al.* (2009) show for the case of wireless internet technology that standardization was essential for reducing uncertainty about competing technologies and therefore facilitated the subsequent commercialization and improvement of technological applications. Standardization is therefore not only a measure of diffusion, it also captures the coordination of firms' strategies, industry-level entry and exit and the formation of expectations about the upcoming introduction of new products and production processes. The nature of standards as signalling mechanisms is closely linked to the literature on the role of news for macroeconomic fluctuations (Jaimovich and Rebelo, 2009; Beaudry and Portier, 2006).

Economic significance and "lumpy" adoption. 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. In comparison to patents, standards capture networks effects at the industry level and therefore comprise a high degree of economic significance. The release of a standard by a standard setting organization is the outcome of a process of lengthy negotiations. Due to compatibility and the high degree of technological detail, a standard represents very often many inventions and is linked to several other standards. Judging by technological content, a standard is therefore more aggregated than a patent. Standardization is a temporally concentrated adoption of bundles of complementary inventions and thus captures the concept of major innovations or new generations of technology coming in "jumps".

Discontinuous technologies which incentivize incremental innovation. Once a standard is issued, firms adopt it (gradually) and thus replace old vintages of technology with a new one. In the spirit of the *radical vs. incremental innovation* dichotomy[9] found in the literature of innovation economics, we interpret our measure of technological change as one that captures radical/discontinuous technologies. This is motivated by the finding of Bekkers and Martinelli (2010) who show that standardization processes coincide with the creation of new technological opportunities and trajectories (Dosi, 1982). A *discontinuous* technological innovation is the starting point of a technological trajectory along which *continuous* innovations are constantly introduced until a new technological paradigm emerges. A standard defines a new technological basis which is often characterized by backwards non-compatibility. For instance, 2G is not compatible with 1G and neither is 3G compatible with 2G. This necessitated substantial, costly investment into interoperability and new infrastructure such as network towers. The adoption of a radical innovation leads to the need for the development of incremental innovations and applications. Standards therefore play an important role for endogenizing inventive activity. This is due to the fact that standardization lays an important foundation for investments in follow-up inventive activity building upon the common technological basis.

Long-term impact of technology choices. Standards are intimately linked to current and future innovation: not only is one technology selected among a number of existing technologies, but standardization increasingly defines what needs to be invented in the future. 4G technology, though a marketing buzzword in the ICT sector, has not yet been introduced to the market. However, the need for future 4G technologies was already identified years ago and standards are currently set in order to facilitate the development and market introduction of these technologies. Standards "lock" an industry into a specific technology. The impact of such "QWERTY-nomics" (David, 1985) is substantial for future developments since network externalities, path dependence and irreversibility of investment make future technology a function of today's standardization choices.

Definition and nature of technology (adoption) shocks

When using a direct indicator of technological diffusion, it is important to specify what actually constitutes a technology shock. The macroeconometric literature which identifies technology shocks using long-run restrictions, is extracting a shock process which has permanent effects on productivity and output. Although this literature interprets these shocks mainly as technological change in its literal meaning, the identified shock comprise *any* shock that leads to higher productivity in the long-run. It is thus a weighted average of technological change, but also political reforms (Aguiar and Gopinath, 2007), changes in social attitudes or taxation (Uhlig, 2004). However, each of these components merits a separate treatment as their transitory dynamics can be expected to differ considerably.

[9] See Garcia and Calantone, 2002 for a discussion.

A technology shock in the context of this paper is directly concerned with technological change, i.e. it is a shock to the distance between the technology frontier and currently adopted technology which manifests itself by an increase in technological standardization. However, technology diffuses slowly. Following standardization, machines and production processes are only replaced gradually which results in a S-shaped diffusion curve. The bulk of actual changes in aggregate macroeconomic variables is therefore only observed after several periods.

Standardization is a highly complex technological phenomenon; however, it is not a black box despite the large number of innovations comprised in each standard. Strictly speaking, each data point could be related to a specific decision by standardizing firms. The arrival of inventions and scientific innovations is very difficult to time exactly. However, the decision to adopt a technology can be timed very precisely by adopting firms and thus constitutes an intentional *economic* decision. It is therefore only a logical consequence that technological standardization is characterized by discrete jumps. Moreover, important network effects and technological interdependencies call for the clustered adoption of technologies. Standardization constitutes therefore a channel of technology adoption which discretizes an otherwise smooth technology supply. Thus, adjustment to the technology frontier *has to* happen occasionally due to the very nature of technological progress.

Standards are mainly a phenomenon of the ICT industry. Complex and systematic technologies lead to the need for standardization. We are therefore identifying a *specific* technology shock which is interpreted as one of radical technical change. Technical change that is rather incremental or happens at the plant level such as organizational restructuring or managerial innovation is not the focus of our analysis. Although we are concentrating on ICT, our aim is to uncover general mechanisms that are characteristic of technological diffusion. The fact that ICT has constituted *the* dominant technology in recent decades motivates the approach.

3 Literature

Embodied technology and productivity dynamics

The importance of (embodied) technology for growth is not contested in the economics profession; however, its effect on short-run fluctuations is not as clear cut. The short-run effect of technology is an issue which has mainly been tackled in the vintage capital literature which stresses the impact of embodied technological change on macroeconomic aggregates. For example, Campbell (1998) and Dwyer (1998) show that firm entry and exit are functions of embodied capital. This literature not only looks at the effect of technological change on growth, but explicitly analyzes the transitory dynamics of firm-level output and in particular productivity.

One strand of the vintage capital literature emphasizes the negative transitory effect on productivity due to learning and incompatibility of new with existing technology (Hornstein and Krusell, 1996; Cooley *et al.*, 1997; Greenwood and Yorukoglu, 1997; Andolfatto and MacDonald, 1998). The adoption of new technologies leads to short-run fluctuations of macroeconomic aggregates as resources are diverted to reorganization of production and skill development in order to use new technologies efficiently. 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”. Yorukoglu (1998) finds that the introduction of ICT requires a huge 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 incompatibility of new ICT technologies with existing expertise.

Though technology and productivity are often considered to be the same thing, the translation of the former into the latter is not straightforward. Acemoglu *et al.* (2012) analyze the interactions between innovation, investment in learning related to new technologies, and productivity growth. They define the diffusion process by which a new technology spreads through the economy as standardization. Innovation and standardization are complementary drivers of productivity growth. Nevertheless, excessive standardization can be an impediment to innovation and slow down productivity growth as innovators’ rents are reduced.

Endogenous productivity

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 a *stochastic* technology supply. However, it is not straightforward why technology should be more exogenous than any other component of the cycle. Furthermore, microeconomic analysis of R&D spending and patenting has consistently found that these measures are endogenous to economic variables.

The literature on R&D and patenting identifies three mechanisms that make innovative activity a function of the cycle: (1) economic incentives and demand effects, (2) the role of financing costs and (3) the opportunity cost hypothesis. *First*, demand effects such as the limited absorptive capacity of markets and profit-seeking can lead to innovative activity being procyclical. This is in line with the evidence presented in Geroski and Walters (1995) who show that technologies are adopted in clusters which coincide with economic booms. Francois and Lloyd-Ellis (2003) build a theoretical model which relies on the endogenous clustering of technology implementation due to entrepreneurs which seek delay of adoption until the time of an economic boom in order to realize high rents. Shleifer (1986) shows how firms prefer to introduce new technologies in booms because profits from innovation are transitory due to imitation by competitors. Barlevy (2007) applies a similar logic to motivate the finding that most of R&D is procyclical.

Second, financing costs might be an important factor for driving both innovation and adoption of new technologies and thus lead to procyclical technology. Ouyang (2011) shows that liquidity constraints are an important factor driving procyclical R&D. However, such mechanisms also play an important role for inventive output and commercialization. For instance, Jovanovic (1995) shows that the costs for the implementation of new technologies outnumber the research costs by a factor of 20.

Third, the opportunity cost hypothesis advocated by Aghion and Saint-Paul (1998) states that investment into R&D and organizational restructuring is more likely to happen during recessions as the opportunity costs of foregone profits are lower during downturns. This theory advocates that technology should be countercyclical. Cooper and Haltiwanger (1993) show that machine replacement is concentrated during times of low labor productivity (such as summer months and recessions) when the replacement in terms of opportunity costs is low. However, these different cyclical forces do not have to exclude each other. Barlevy (2007) shows that pro- and countercyclical channels can nevertheless co-exist, but only the dominant effects - which are the procyclical forces in the case of R&D - will be visible in the aggregate data. Aghion *et al.* (2010) demonstrate that credit frictions can lead to procyclical long-term investment though it would be optimal to have countercyclicality if markets were complete. Aghion *et al.* (2012) and López-García *et al.* (2012) show that the countercyclicality of R&D as a result of opportunity costs can be reversed for those firms which are financially constrained.

Contrary to the literature on endogenous growth (see Rebelo, 1998 for an overview), the idea that productivity could be endogenous has only recently been introduced to business cycle analysis. Insights from the research programme initiated by Zvi Griliches and Edwin Mansfield on the economics of innovation and productivity growth have only slowly found their way into the field. It is especially the empirical finding that technology only diffuses slowly which has been introduced to business cycle models (see for example Rotemberg, 2003, for a first contribution in this respect). Building on the literature on technology adoption, Comin and Gertler (2006) therefore endogenize productivity in a medium-term business cycle model with slow technology diffusion where R&D spending and expenditures for technology adoption vary procyclically.

Technological expectations and news

Standards are defining in which technological direction an industry is heading. Expectations about future technological progress also play an important role for the investment in incremental innovation. Abernathy and Utterback (1978) and the subsequent literature on product life cycles (see Klepper, 1996 for a review) analyze regularities in the process of technological innovation. In this analysis, the development of radical innovations is characterized by rivalry between competing technologies and strong technological uncertainty. When a dominant design emerges, companies reduce their investment in competing technologies, and increasingly invest in incremental innovations building upon the dominant design. The seminal paper by Dosi (1982) similarly stresses the importance of emerging "technological paradigms" as a stepping stone for further technological progress. Product innovation is thus gradually replaced by process innovation. News signalling the emergence of a dominant design therefore serve as expectational anchors and encourage investment in new technologies which share a common technological basis.

It is therefore interesting to investigate inasmuch standards which signal the arrival of a new "technological trajectory" (Bekkers and Martinelli, 2010) are actually perceived as a device of uncertainty reduction and future technological progress. The role of signalling is not totally new to the business cycle literature. Beaudry and Portier (2006) use stock price movements to identify news about the future and show that these lead to an increase in TFP after several years. Consistent with the idea of long diffusion lags, these news shocks are interpreted by the authors as news about technological change which only materializes and leads to productivity increases after a long process of adoption. The theoretical counterpart of this idea is analyzed in Jaimovich and Rebelo (2009) who propose a model that includes news shocks which have an impact on productivity only in the future. Comin *et al.* (2009) model the idea of news shocks leading to TFP change by explicitly associating expectations about the future with fundamental technological changes in a model of endogenous technology adoption.

4 Description of the data

4.1 Data sources

The empirical identification of technology shocks is a crucial methodological challenge. We make use of patent and standard time series. For the latter, we use the PERINORM database and collect formal standards which are released in the United States. The standard time series include all formal industry standards issued by American standardization bodies, such as ANSI, as well as international standard organizations issuing standards that apply to the US. For a small 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 assuming the same quarterly distribution of these standards as for the one for which we have the complete date of release. Working with the standard series that only comprises standards with the full date does not change our results.

Regarding patent data, we compiled time series of patent applications at the USPTO and PATSTAT, including applications by American as well as foreign companies. We therefore include inventions that are likely to be commercialized in the US independently of their origin. We use the date of application (and not the grant or priority date). In addition we use the originality indices from the NBER patent database. For both patents and standards, we use data on the aggregate level (utility patents as well as manufacturing and services standards) and for the ICT sector. For the sectoral ICT data, we use the ICS (International Classification of Standards) classes 33 and 35. For patents, the PATSTAT categories G and H as well as USPTO's category 2 are used.

For the macroeconomic data, we employ time series from the NIPA tables from the Bureau of Economic Analysis (BEA), in particular non-residential investment in equipment and software. We use different output measures: (1) non-farm business output from the Bureau of Labor Statistics (BLS), (2) the industrial production index (IPI) for communications equipment as well as the (3) the IPI for computer and electronic products, both from the Federal Reserve Board, and (4) the Tech Pulse index from the Federal Reserve Bank of San Francisco. Our measure of TFP adjusted for capacity utilization is from John Fernald of the Federal Reserve Bank of San Francisco. In particular, we use the TFP index for the equipment and consumer durables sector, but results do not change if the aggregate index is used. Finally, we use the S&P 500 stock market index. All data are quarterly for the period 1975Q1-2010Q2.

4.2 Cyclical patterns

In figure 2, we plot the untreated data for patent counts and standards in both the ICT sector and for all ICS classes. The standard series is substantially "lumpier" than the patent series. 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 actions. 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 due to its microeconomic nature not subject to the same degree of aggregation as typical macroeconomic series. Figure 2 also shows that the standard series for ICT and for all ICS classes differ substantially despite the former being part of the latter.

R&D and patenting have been found to be procyclical. Figure 3 plot the time series for R&D expenditures and ICT patent counts against output. A clear cyclical pattern emerges especially for the time period from 1985 on and thus strongly suggests that demand effects and liquidity costs might be important factors driving innovative input. Since standardization is a costly adoption process, we ask whether the results of the literature on R&D and patenting also carry over to technology adoption. We therefore explore the cyclical patterns of our new indicator and plot detrended non-farm business output as well as detrended and smoothed ICT standards[10] in figure 4 for the period 1975Q1 to 2010Q2. The plot implies that standardization, and thus technology adoption, is also procyclical.

Cross-correlations can give some information on the timing of this procyclicality. Figure 5 shows that both output and investment lead our smoothed standardization series by

[10] 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 5 quarters.

four quarters which indicates that the procyclicality of technology might actually be due to technology being cycle-driven. The correlation coefficient of around 0.5 suggests that this effect might be even quite decisive. TFP adjusted for capacity utilization is lagging standardization by one quarter and is positively, but not very strongly correlated with standardization.

The procyclical feature of standardization as displayed in figures 4 and 5 could stem from three different explanations: (1) technology adoption has a positive impact on output, (2) technology adoption is procyclical as it is driven by the cycle or (3) causality runs in both directions: technology adoption is driven by the cycle but also generates a feedback on macroeconomic variables. We will therefore investigate inasmuch the patterns described here survive the test of more rigorous, structural analysis.

5 Econometric strategy

5.1 A Bayesian VAR which accounts for long diffusion lags

Since we are interested in the dynamic interaction between technology and macroeconomics, we employ a vector autoregression model. The effect of innovation and adoption of technology on macroeconomic variables is characterized by long diffusion lags. For this reason, a large number of lags has to be incorporated into the VAR. In order to deal with overparameterization, we opt for a Bayesian VAR approach where the decay of the lags of each variable (except the technology variable) is restricted to zero with a prior. A Minnesota prior is imposed where the prior coefficient matrix for macroeconomic variables mimics their unit root properties and the one for technology adoption assumes a white noise behaviour.

We use a Bayesian approach in order to allow for a differentiated lag structure among the variables in the VAR. The Minnesota prior assumes that own lags are more informative and that longer lags are less relevant. We impose a non-decaying prior variance for the technology variable since we have strong *a priori* beliefs that the effect of technology on specific macroeconomic variables is characterized by long lags (Mansfield, 1968). We therefore do not assume a decaying prior variance for the coefficients of lagged technology, but "let the data decide". The low autocorrelations of the standard series motivate this assumption. All equations are treated symmetrically (Kadiyala and Karlsson, 1997; Sims and Zha, 1998) as the treatment of the prior variance of the technology variable is imposed both on the equations of macroeconomic variables as well as on its own equation. Denoting technology with the letter k, the informativeness of the prior is therefore set as follows:

$$V\left(a_{ijl}\right)=\begin{cases}\dfrac{\phi_1}{l^{\phi_4}} & \text{for} \quad i=j,\ i\neq k,\ l=1,\ldots,p \text{ (own lags, except technology)}\\ \dfrac{\phi_1\phi_2}{l^{\phi_4}}\dfrac{\sigma_i^2}{\sigma_j^2} & \text{for} \quad i\neq j,\ i\neq k,\ l=1,\ldots,p \text{ (lags of other variables)}\\ \phi_1\phi_2\dfrac{\sigma_i^2}{\sigma_j^2} & \text{for all } i,\ j=k,\ l=1,\ldots,p \text{ (lags of technology)}\\ \phi_3\sigma_i^2 & \text{for the constant}\end{cases}$$

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 such as the Normal-Wishart prior have to be used.[11] Therefore, 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 (see Bańbura *et al.*, 2010 for an example). The weight corresponding to each of the dummies corresponds to the respective prior variance.

The vector $\phi = (\phi_1\ \phi_2\ \phi_3\ \phi_4)$ denotes the hyperparameters which govern the "tightness" of the prior. We assume a quadratic decay of lag importance as is common in the literature and thus set $\phi_4 = 2$. The prior on the constant is assumed to be uninformative. Since the implementation of a Normal-Wishart prior requires a symmetric treatment of all equations (Kadiyala and Karlsson, 1997; Sims and Zha, 1998), the hyperparameter ϕ_2 has to be set to 1. We set a relatively loose value for ϕ_1 as we want to let the data "speak" as much as possible. We also experimented with different values for ϕ_1 and results did not change quantitatively.

5.2 Identification of shocks

A technology shock in the context of this paper is defined as a discrete catch-up with the technology frontier. 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 decision to select one of the existing technologies for standardization and thus commercialization is on the one hand determined by the cycle and on the other hand determined by the distance to the technology frontier. This distance is (partly) exogenous

[11]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).

and can provoke a 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. Moreover, standardization is a form of technology adoption which is characterized by "lumpiness" since many inventions are comprised in one standard and in turn many standards are adopted at the same time due to network effects. Thus, even if the technology frontier is evolving rather smoothly (assuming that science is constantly producing innovative output which is characterized by low-frequency variation), the lumpy and clustered adoption of new technologies leads to discrete technology shocks which vary at high frequencies.

The literature on technology shocks has mainly relied on long-run restrictions for the identification of technology shocks. This literature works with "derived" technology shocks. In the case of the present paper, however, we have direct access to an indicator of technology adoption and thus want to exploit this data without imposing how technology shocks affect certain variables in the long-run, but rather let the data speak. Moreover, by avoiding to rely on long-run restrictions, we assure that we are not confounding technology shocks with any other shocks that have a permanent effect on macroeconomic variables. It is for this reason that we use a Cholesky identification scheme which imposes minimal assumptions on the contemporaneous impact of shocks. Since standardization is the first step of the actual implementation of a new technology and since technology diffusion is a slow process, we order standards last in our VAR assuming that a technology shock, i.e. a shock to the distance between currently adopted technologies and the technology frontier, only affects standardization contemporaneously.

In order to analyze the response of standardization to the business cycle, we investigate its reaction to a "business cycle shock". This identification strategy follows Giannone *et al.* (2012). 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. Similar procedures using forecast error variance decompositions have been used by Barsky and Sims (2011) and Uhlig (2004). In particular, our "business cycle shock" is derived using frequency domain analysis and its detailed derivation is described in the appendix.

6 Discussion of results

In the baseline model, our VAR system is composed of four variables: non-farm business output, non-residential investment in equipment and software, total factor productivity in the equipment and durables production sector which is adjusted for capacity utilization, and finally standard counts. For the estimations, all data are in log levels and collected at a quarterly frequency for the time period 1975Q1-2010Q2. As already mentioned above, 12 lags are included in the VAR system since technological progress is characterized by long diffusion lags.

6.1 Endogenous technological innovation and adoption

Empirical evidence has shown that R&D is procyclical on the agreggate (Barlevy, 2007; Ouyang, 2011; Aghion *et al.*, 2012) as is patenting (Griliches, 1990). Our emphasis, however, lies on the analysis of the actual *implementation* of new technologies. The process of standardization does not come without cost as firms need to invest into the adoption of new technologies, replace old standards and potentially increase human capital effort. Costs also accrue to users (manufacturers and service providers) and final consumers. The decision to standardize is ultimately a costly decision to catch-up with an ever-evolving technology frontier. Standardization is thus a positive function of the distance to this frontier as well as a positive function of the cycle. According to this hypothesis, the procyclical time series patterns in figure 4 are not, or not only, due to technology driving the cycle (as the RBC conjecture predicts), but causality actually also runs from the cycle to technology.

Figure 6 displays the responses of standards to shocks to a business cycle shock. Figure 6 shows that technology *adoption* is also cycle-driven. The response of standardization to an output shock is positive and significant in the medium-run and peaks around 10 quarters. In much of the macroeconomic literature, scientific innovations are assumed to appear randomly from nowhere (which is already a strong simplification given procyclical R&D and patenting); however, the results point to the important role of demand effects and financing costs for the actual implementation of technological progress. This finding seriously challenges the idea of technology being exogenous.

Interestingly, this effect holds more for the aggregate cycle than for sectoral measures (see figure 7). We substitute our measure of output with sectoral data and identify a "sectoral business cycle shock" in the same way as the aggregate one. The fact that the aggregate cycle, as opposed to sectoral indicators, leads to a significant pick-up of standardization indicates that high adoption costs (Jovanovic, 1995) and liquidity constraints are an important determinant of technology adoption. Ouyang (2011) shows that R&D is substantially less procyclical at sectoral than aggregate level and argues that liquidity constraints are a key driver of this phenomenon. Our result is also in line with the evidence presented in Geroski and Walters (1995) who show that innovations are adopted in clusters which coincide with economic booms.

Figure 7 plots the response of ICT standards to different shocks to sectoral and aggregate output. In contrast to output, the reaction to a shock to the Tech Pulse index, an index of overall "health" in the information technology sector in the US, is muted. There is even a slightly negative reaction to the industrial production indices of the computer and electronics sector and the communications equipment sector. The fact that the latter are leading to a decrease in standardization point to a lock-in effect of technologies which are radical rather than incremental. When production and investment in technological sectors are high, incentives are lower to switch to a new technology which will make the current one obsolete. Rent-seeking technology producers will try to exploit the profitability of their products (Shleifer, 1986; Francois and Lloyd-Ellis, 2003).[12] A lower incentive to adopt new (incompatible) technologies once a large investment into existing technology is made and suggests a lock-in effect of the installed base on technology adoption.

6.2 Transitory dynamics: TFP and the cycle

What happens following a technology shock?

Figure 8 displays the impulse responses to a technology shock. The reaction of output is positive and displays an S-shaped initial response as does investment. This shape is indicative of typical processes of technology diffusion (Griliches, 1957; Jovanovic and Lach, 1989; Lippi and Reichlin, 1994). Investment in equipment and software reacts positively. This reaction confirms our interpretation of standards as a measure of technological implementation. Standardization facilitates the identification of new technologies and reduces technological uncertainty. Investment in new equipment is therefore not only valuable as new technologies are being commercialized; standardization also assures the compatibility with future technologies.

Our indicator of investment picks up inasmuch the implementation of new technologies is mirrored by an increase of investment in equipment and software. In order to explore aggregate effects as well as which parts of investment are concerned the most, we replace our measure of investment in equipment and software by a measure of aggregate non-residential investment as well as the breakdown of information processing equipment and software which is part of the overall equipment and software series.

Table 1: Impact of a technology shock, in % at horizon 20

Series	**IRF**
Nonresidential investment	0.86
Equipment and software	1.62
Information processing equipment and software	1.50
Computers and peripheral equipment	2.49
Software	1.24
Other	0.47
Industrial production index	0.68
Nondurables	0.58
Durables	0.71
Computer and electronic product	1.73
Computers and peripheral equipment	3.40
Communications equipment	3.32

The increase in investment is about double for equipment and software than for the

[12] Another explanation of the different reaction to aggregate and sectoral output shocks could be the opportunity cost hypothesis (Aghion and Saint-Paul, 1998) as explained in section 3.

total of non-residential investment. Most of the increase is due to investment in computers and peripheral equipment (2.49% vs. 1.27% for investment in software.) Similar sectoral patterns are found when replacing the output measure with different sectoral industrial production indices. The fact that the overall economy is investing in new equipment and software is reflected by an higher output of the ICT sector.

Quantitative importance of technology shocks

The early RBC literature attributed a very large share of variations in aggregate fluctuations to “technology shocks”. Though the RBC conjecture has been criticized extensively, 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, 1997). However, evidence on the role of IST shocks for business cycle fluctuations is mixed.[13]

At business cycle frequencies (8 to 32 quarters), our identified technology shocks only contribute to a small extent to output or investment; the results are more meaningful for TFP.

Table 2: Variance decompositions at different frequencies

	Business cycle shock		Technology shock	
Frequency (quarters)	8-32	2-200	8-32	2-200
Output	0.67	0.38	0.08	0.19
Investment	0.34	0.23	0.09	0.15
TFP (adj.)	0.17	0.19	0.15	0.15
Standards	0.16	0.17	0.62	0.66

The above results indicate that the contribution of our identified technology shocks are far from what is sometimes found in the IST literature (let alone the early RBC literature). However, the conceptual interpretation of what constitutes neutral technology or IST shocks is extremely broad.[14] For instance, IST shocks are identified somewhat agnostically (similar to neutral technology) which is mirrored in the fact that the entire IST literature identifies shocks using the relative price of investment. Price data, however, should reflect

[13]Greenwood *et al.* (2000) find that 30% of business cycle fluctuations can be attributed to IST shocks. Fisher (2006) finds that 42% to 67% of output fluctuations are driven by IST shocks. A similar value of 50% is found by Justiniano *et al.* (2010). On the other hand, Smets and Wouters (2007) find substantially smaller values. Defining investment shocks as the rate at which consumption goods are transformed into investment goods, Justiniano *et al.* (2011) and Schmitt-Grohé and Uribe (2012) find that investment shocks do not contribute to business cycle volatility. However, shocks to the rate at which investment goods are transformed into installed capital are found to be important drivers of business cycles.

[14]Neutral technology shocks are generally accepted as a black box and “measure of our ignorance”, but even IST change is interpreted differently in the literature. Whereas one part of the literature clearly associates IST shocks with technological change (Greenwood *et al.*, 1997, 2000; Fisher, 2006), others interpret IST shocks as demand shocks (Smets and Wouters, 2007) or associate elements of it with financial frictions (Justiniano *et al.*, 2011).

both technological change as well as demand effects or changes in the competitive market structure. Justiniano *et al.* (2011) show that an identification based solely on data of the relative price of investment will confound several of its determinants of which technological change is just one among many. This paper, on the contrary, identifies a very specific technology shock which is not a black box. We do not claim that other "technology shocks" such as policy changes, organizational restructuring or human capital are 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. The fact that we are isolating a "true" technology shock could explain the magnitude of the decompositions. In addition, the above results are comparable with the ones of Alexopoulos (2011) in terms of the contribution of technology shocks to aggregate volatility.

Decomposing the variances at different frequencies is instructive for understanding which frequency component of the data is influenced by the shocks. From table 2, and more so from figure 9, it is obvious that technology shocks play a more important role for investment and output at lower frequencies which is something one would expect from growth theory. The effect of a technology shock on TFP is both important at business cycle frequencies and in the long-run. The decompositions are consistent with the idea that the introduction of a new technology causes organizational changes in the short- and medium-run on the industry and plant level, but that its aggregate effects on the macroeconomic cycle matter only in the long-term.

A closer look at 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. On the contrary, *neutral* technology shocks as represented by TFP are a measure of *disembodied* technological change.

Figure 8 shows that TFP falls below trend following a shock to technology adoption. Even when a technology is adopted by firms, an immediate pick-up of productivity cannot be taken for granted. On the contrary, there is a microeconomic literature which shows that labour productivity can slow down following the introduction of a new technology due to learning and human capital mismatch as well as due to the incompatibility of the new technology with the installed base (Farrell and Saloner, 1986). This incompatibility concerns as well human and organizational capital as well as physical capital. Standardization has nevertheless an important implication for future technological progress. Innovative applications are built upon standards as a common technological basis: an important investment must be made in *incremental* innovation and in the construction of compatible physical capital in order to exploit the technological potential of the new *fundamental* technology (the standard). After a standardization shock, TFP can therefore temporarily decrease, before the implementation and deployment of the new technology raises the level of productivity permanently. Our work can therefore be related to the vintage capital literature which identifies discontinuous technological change as a driver of temporary slowdowns in productivity (Samaniego, 2006; Greenwood and Yorukoglu, 1997; Yorukoglu, 1998).

Our finding casts doubt on macroeconomic models which neglect the microeconomic mechanisms involved with technology adoption and 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. Interestingly, our response of TFP shows a strikingly similar shape as the one of Beaudry and Portier (2006) who identify technology shocks by very different means and variables.

Explaining TFP is a challenging task as it is constructed as an unexplained residual. Historical decompositions allow us to assess the quantitative contribution of various shocks over time. Figure 10 displays these decompositions for our TFP measure. The series are simulated by only considering technology shocks on the one hand and only allowing for business cycle shocks on the other hand. Interestingly, the historical decompositions for TFP perform very much in favour of technology shocks which even seem to outperform business cycle shocks. Though not every spike in TFP can be accounted for by our technology shock, the contribution of technology shocks is quite substantial until the second half of the 1990's. This can be interpreted as another important evidence for the role of embodied technological change for disembodied productivity.

6.3 Technological change and expectations

Figure 8 shows that the effect of technology adoption on the cycle is characterized by slow diffusion. However, the effects generated by technology adoption on the firm and industry level should have an important impact on growth, if not the cycle: if tangible macroeconomic effects "only" materialize as changes in aggregate productivity, but short-run effects on output cannot be detected, is the information on technology adoption leading to higher *future* growth nevertheless incorporated by financial markets? We therefore ask if technology adoption shocks are comparable to "news shocks".

Beaudry and Portier (2006) use stock price movements to identify news about the future and show that these lead to an increase in TFP after several years. These news shocks are interpreted by the authors as news about technological change which only leads to productivity increases after a long process of adoption. We therefore add the S&P 500 index, deflated by the seasonally adjusted implicit price deflator of nonfarm business output, as a last variable to our VAR. The results in figure 11 show that the stock price index reacts positively to an adoption shock and thus confirm that financial markets pick up the positive news about future productivity increases despite an initial decline in TFP which is caused by the incompatibility of new technologies with existing capital.

The fact that financial markets pick up the long-run positive effect of technology adoption on TFP in the short-run shows that standards anchor expectations. We therefore also want to explore inasmuch standardization can lay the ground for further incremental innovation by reducing uncertainty which persists as long as competing inventions and technologies co-exist. Once a dominant technology is chosen, incremental and continuous innovation building upon the common technological basis can pick up. We run a VAR with output, investment, patents and standards for which the results are displayed in figure 12. Patents do not lead to an increase in standardization which could be due to the fact that the economic significance of many patents is very low and that the time from the date of application until the grant date amounts very often to many years, not to mention the time it takes for a patented invention to actually be implemented. Interestingly, patent application counts react positively to a standardization shock. Our result compares to the one found by Gandal *et al.* (2004) who show that participation in standardization meetings Granger causes patenting, but not vice versa. They interpret this finding as an indication that only the most recent innovations are treated in standardization committees and that the latter are an important mechanism for knowledge diffusion. Similar dynamics are identified by Rysman and Simcoe (2008) who show that patent citations increase following standardization. We interpret the positive reaction of patents to standard shocks as an indication that standardization can lead to further incremental innovation. This is consistent with the idea that the majority of R&D is actually spent on development, rather than on research (Griliches, 1990).

We explore this idea further by looking at the originality index of the NBER patent database. The goal of this exercise is to side-step the problem that many patents have a very low economic significance. The originality index measures the dispersion of citing patents over technology classes and therefore indicates that the patent has been important for a broad field of further research (see Hall *et al.*, 2001 for the methodological issues). We extract both the originality index for ICT as well as for all patent classes. The time series are too short for a full-fledged structural analysis (1980Q4 - 1999Q2), but cross-correlations give a first indication about patenting patterns. Figure 13 displays the cross correlations of the four quarter moving averages of originality index and patent applications for both ICT and all technology classes. The originality index, a measure of the importance of a patent for future research, is leading patent applications. Higher innovative activity today can be associated with higher patent applications tomorrow. We interpret this correlation in the light of our results on standard-patent dynamics as indicative of the fact that patenting reacts to fundamental changes in technology.

Another explanation for the pick-up of patenting following standardization concerns the strategic value of patents for firms. Patents are often understood as the innovative output of R&D. However, patenting is more and more an entrepreneurial decision rather than an innovative result: With much of nowadays' innovation being dependent on existing technology, it is difficult to clearly limit the scope of a patent. Firms want to avoid paying royalties or fines for patent infringement which is why they try to arm themselves with an arsenal of patents in order to strengthen their negotiation power. Whenever a new technology emerges, it also revives the patent battle. Patenting is therefore not only a symptom of innovative progress, but increasingly, and especially in ICT, an *economic* phenomenon tied to the commercialization of a product.

Standards are essentially an indicator for the coordinated decision to harmonize specific technological advances, to define the fundamental direction towards an industry is heading and thus to make innovations actually usable by a whole market. Standardization can therefore pin down *technological expectations* and reduce uncertainty. By contributing to technological homogeneity, expectations about future technological implementation and compatibility are anchored and as a result, investment in equipment and software increases. In addition, the reduction in uncertainty following a standard shock leads to a pick-up of patenting activity as shown in figure 12. The results from this section stress the point about standards representing a selected adoption of a fundamental innovation which generates further incremental innovative activity and therefore endogenizes the supply of new technologies.

7 Conclusion

This paper seeks not only to answer the ever rebounding question of the role of technology shocks in macroeconomics, but explicitly tries to explain technology as a phenomenon itself. By identifying an important microeconomic indicator which is commonly used in innovation economics, namely technological standardization, we are able to investigate the interaction between the macroeconomic cycle and technology.

Concentrating on 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 radical and discontinuous technology 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 technological frontier which nevertheless increases constantly. The results of this paper show that a clear distinction between embodied, radical technical change and disembodied technology is needed in order to better understand productivity which is essentially a multifaceted phenomenon.

Addressing the question of the exogeneity and stochastic nature of technology, we find that technology, both in terms of invention and more importantly in terms of adoption, is both a determinant as well as a result of macroeconomic fluctuations. In particular, mechanisms such as demand effects and financing constraints make technology a function of the cycle and therefore highlight the important dynamics that characterize this interplay. One aspect of these dynamics is the role of expectations for which standardization is found to be an essential element and driving factor. By reducing technological uncertainty, standardization facilitates investment and lays the ground for future (incremental) innovation.

Our results also help to gain insights about the nature of "news shocks" which are often assumed to appear out of nowhere and are hardly given a structural interpretation. Slow technological diffusion is characterized by similar propagation dynamics and the initial adoption of a new technology which diffuses in an S-shaped manner constitutes a news shock. As shown, standardization is a trigger of technological diffusion and signals to agents that productivity should increase in the future.

Overall, this paper stresses the importance of looking into the microeconomic mechanisms that are at 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 which makes up technology and productivity. 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.* (2012) 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. Starting from a reduced form VAR model

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

it is straightforward to derive its structural representation:

$$\begin{aligned}
B_0 Y_t &= B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + B_p Y_{t-p} + \varepsilon_t \\
Y_t &= (B_0)^{-1} B(L) Y_t + (B_0)^{-1} \varepsilon_t \\
&= A(L) Y_t + u_t && \text{where} \quad A(L) = (B_0)^{-1} B(L) \quad \text{and} \quad u_t = (B_0)^{-1} \varepsilon_t \\
&= [I - A(L)]^{-1} C C^{-1} u_t && \text{where} \quad C = (B_0)^{-1} \\
&= [I - A(L)]^{-1} C \varepsilon_t && \text{where} \quad \varepsilon_t = C^{-1} u_t \quad \text{and} \quad E[\varepsilon_t \varepsilon_t'] = B_0 \Sigma B_0' = I
\end{aligned}$$

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. Assuming a Cholesky identification, 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. However, 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 large enough 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 of finding the rotation matrix R such that $V_{k,j}$ is maximized.

Figures and graphs

Figure 1: The interaction between the business cycle and technology

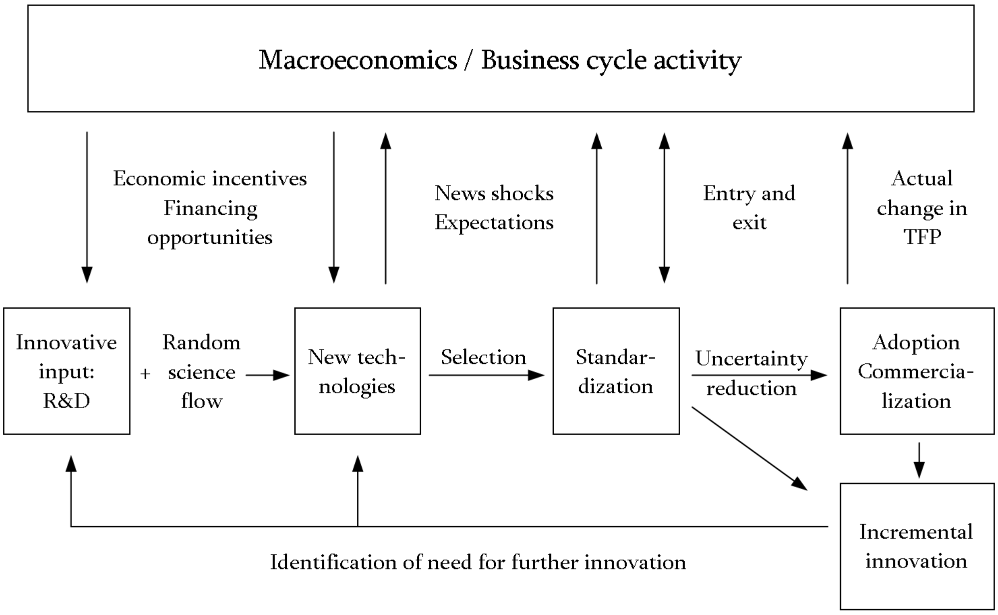
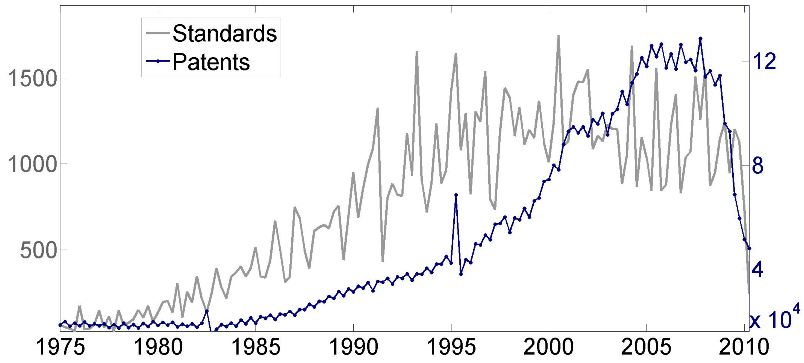
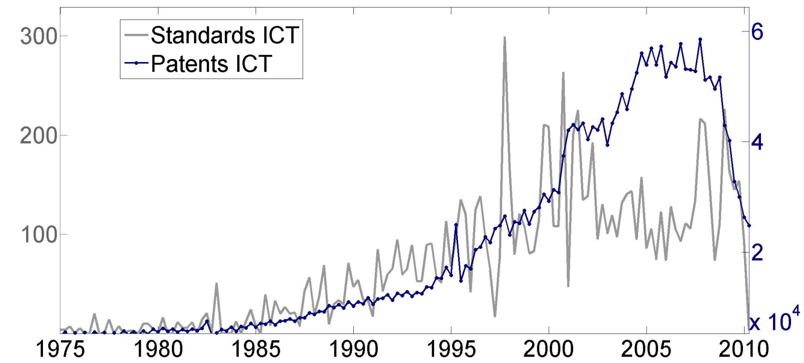


Figure 2: Standard and patent series

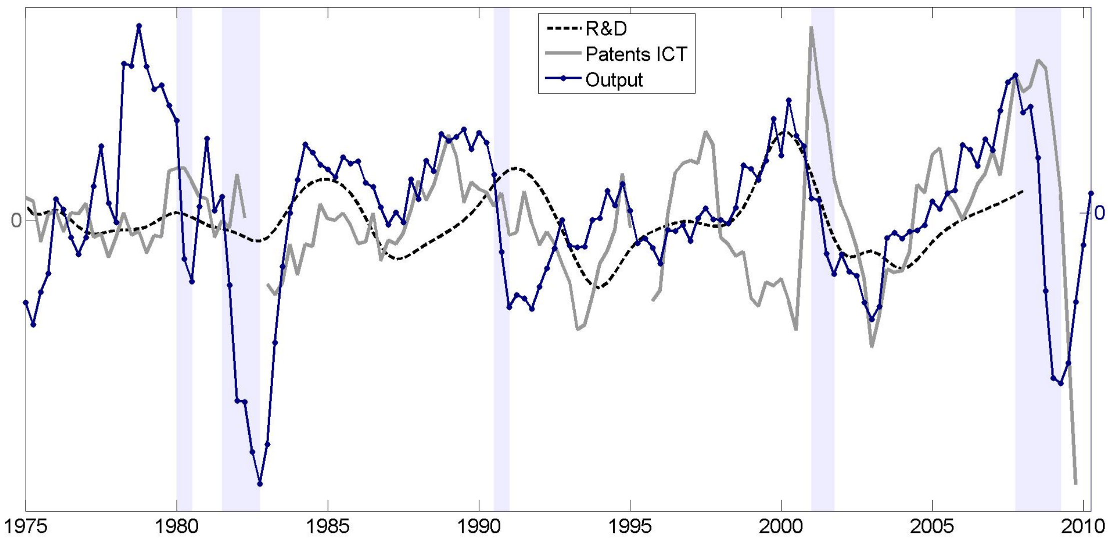


(a) All sectors



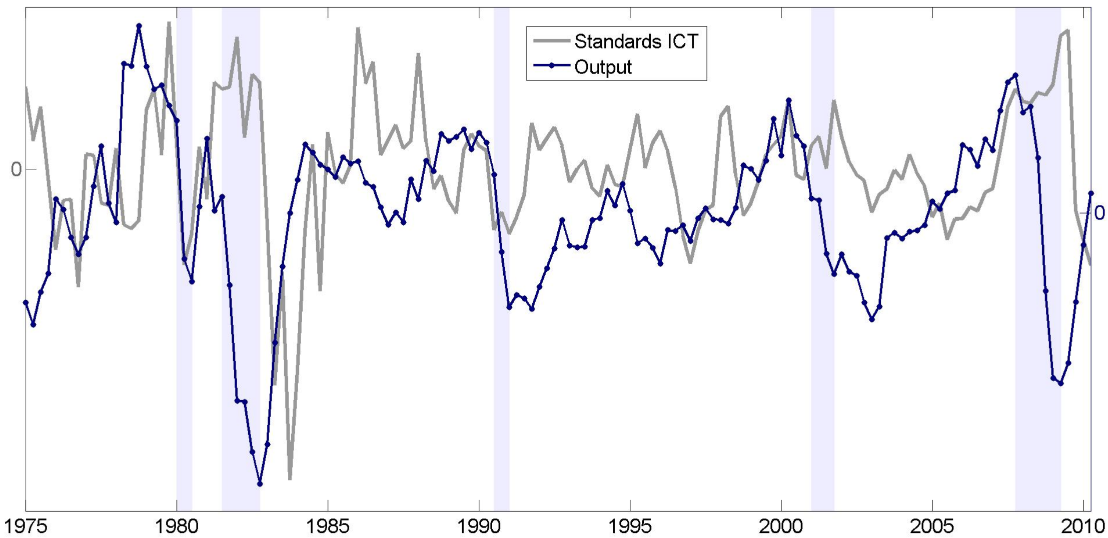
(b) ICT sector

Figure 3: Private R&D expenditures, patent applications and non-farm business output



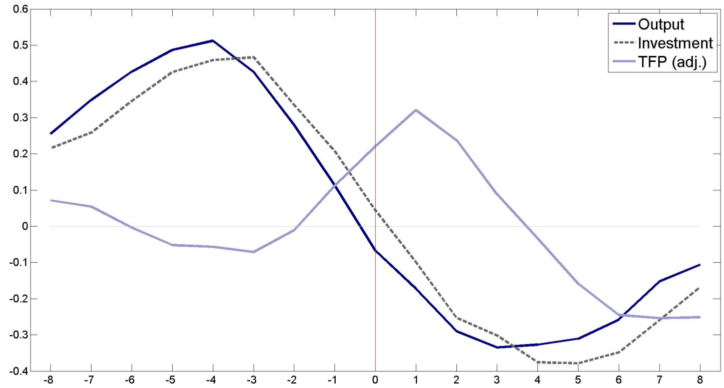
Notes: Data are in logs, seasonally adjusted and HP-detrended (with smoothing parameter 1600). Data for R%D expenditures are only available on an annual basis and therefore interpolated. For the patent series, the data points for 1982Q3-Q4 as well as 1995Q2-Q3 were deleted due to the unusual spikes caused by legal changes in patent law in 1982Q3 and 1995Q2 in order to facilitate the comparison.

Figure 4: ICT Standards and non-farm business output



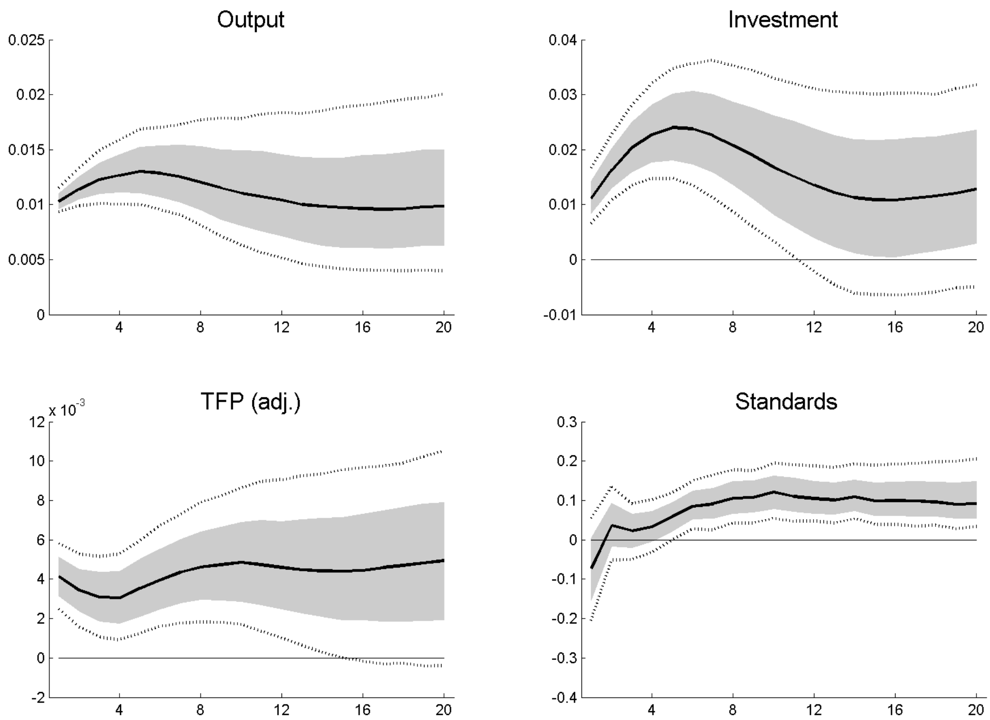
Notes: Data are in logs, seasonally adjusted and HP-detrended (with smoothing parameter 1600). Standard data are averaged over a centered window of 5 quarters. Shaded areas correspond to NBER recession dates.

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



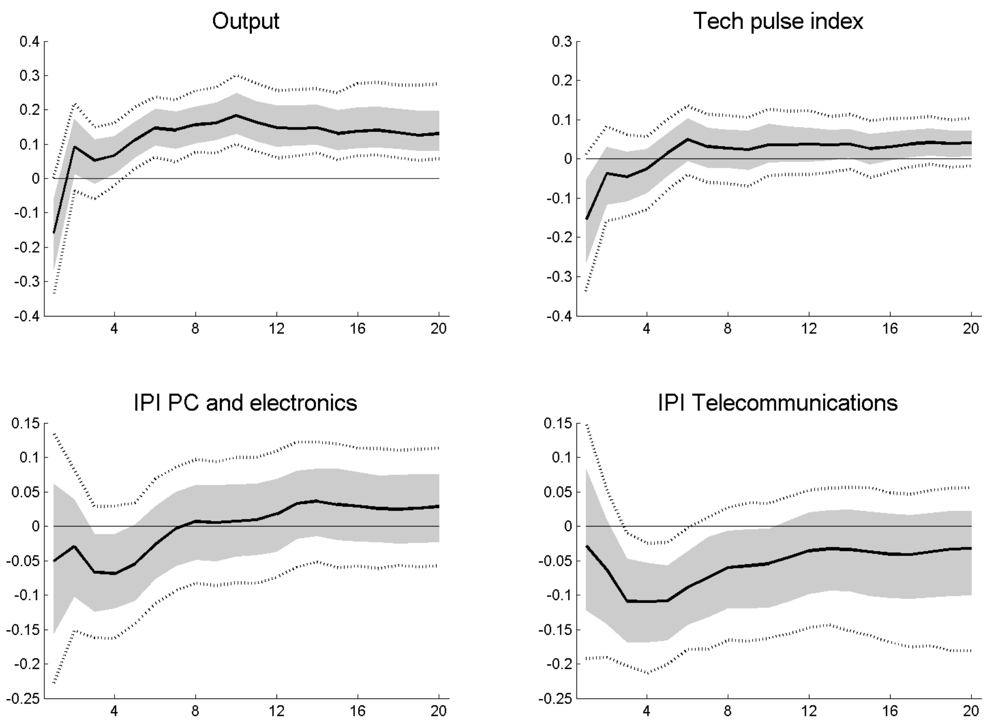
Notes: Cross-correlations were calculated based on the data series displayed in figure 4 (Data are in logs, seasonally adjusted and HP-detrended. Standard data are averaged over a centered window of 5 quarters.)

Figure 6: IRFs: Business cycle shock



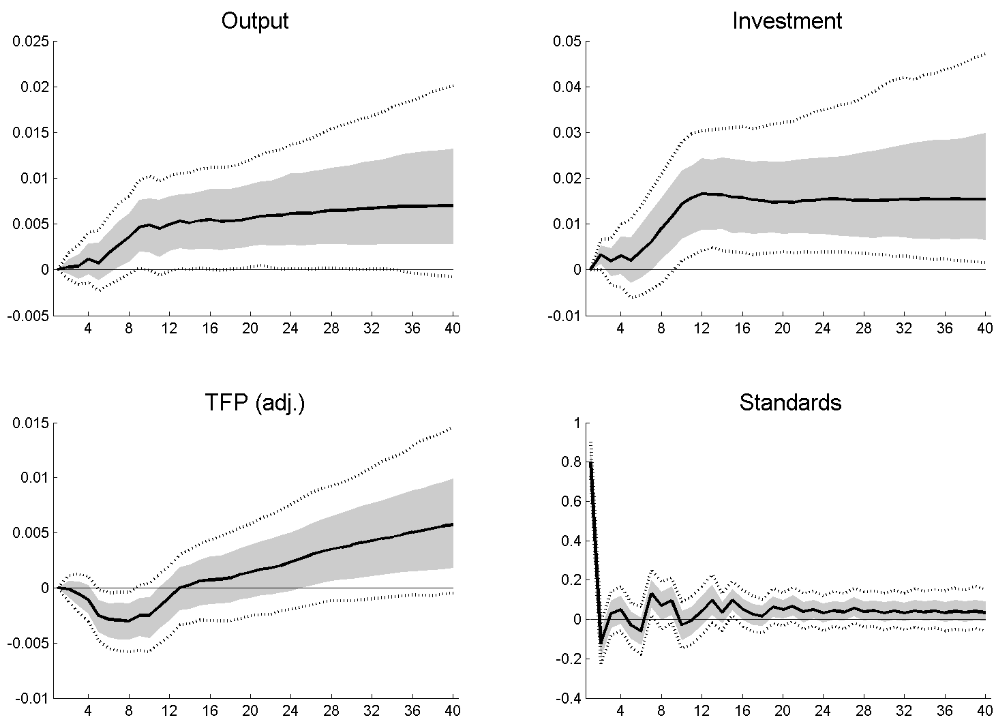
Notes: Impulse responses to a business cycle shock identified as the shock that explains the maximum of forceast error variance of output at business cycle frequencies. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively.

Figure 7: IRFs: Responses of ICT standards to “sectoral shocks”



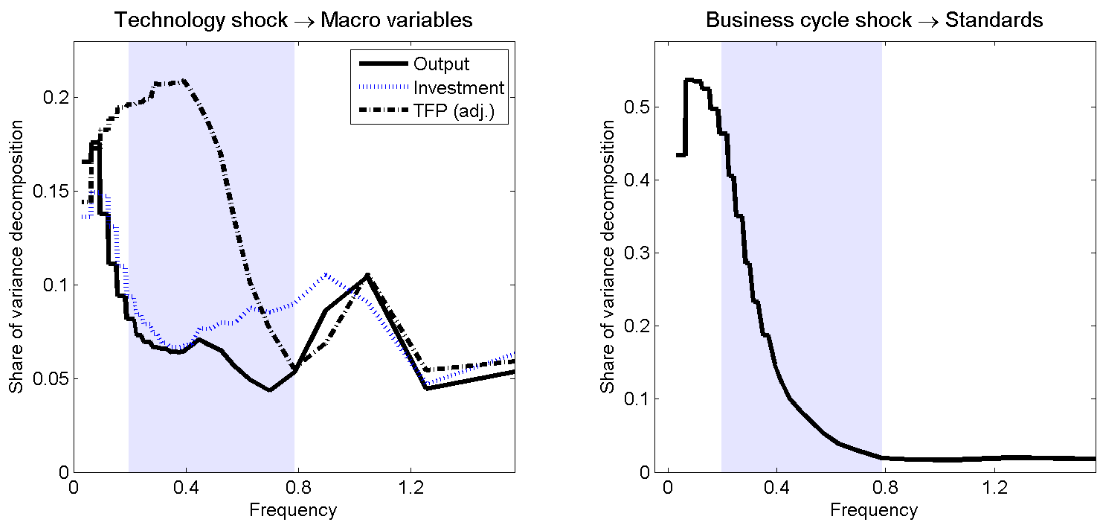
Notes: Impulse responses to different “sectoral shocks”: (1) non-farm business output, (2) Tech Pulse index, (3) IPI for computers and electronic products, (4) IPI for communications equipment. The ordering is: output, investment, TFP and ICT standards. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively.

Figure 8: IRFs: ICT standardization shock



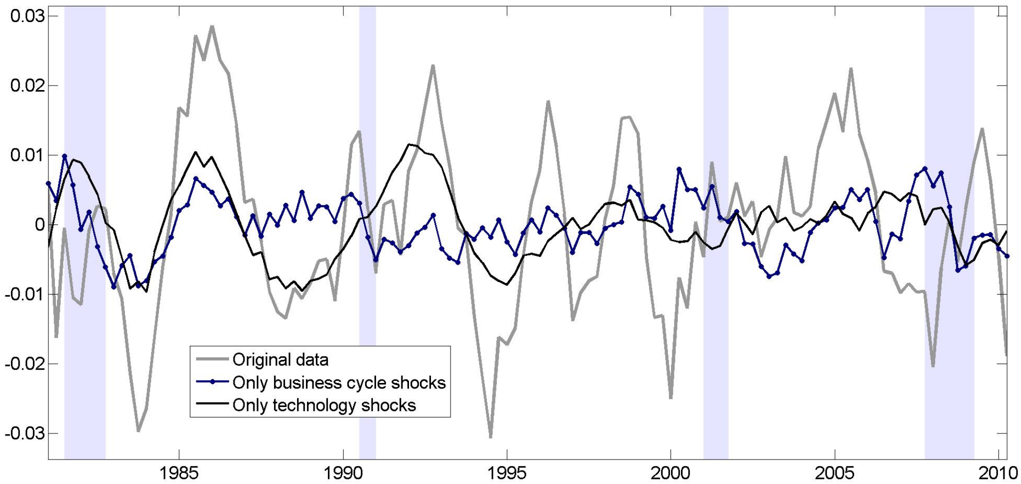
Notes: Impulse responses to a one standard deviation shock to standards. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively.

Figure 9: Variance decompositions for different frequencies



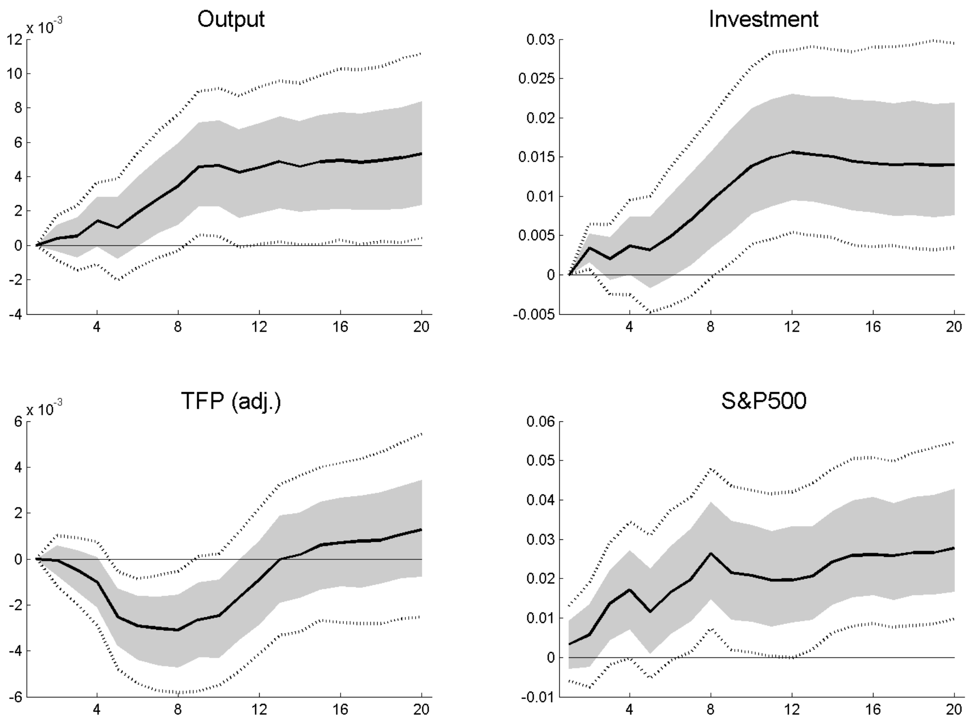
Notes: The variance decompositions refer to the VAR whose impulse response are displayed in figures 6 and 8. The ordering is output, investment, TFP and ICT standards. The shaded region corresponds to business cycle frequencies.

Figure 10: Historical decomposition of TFP (adj.)



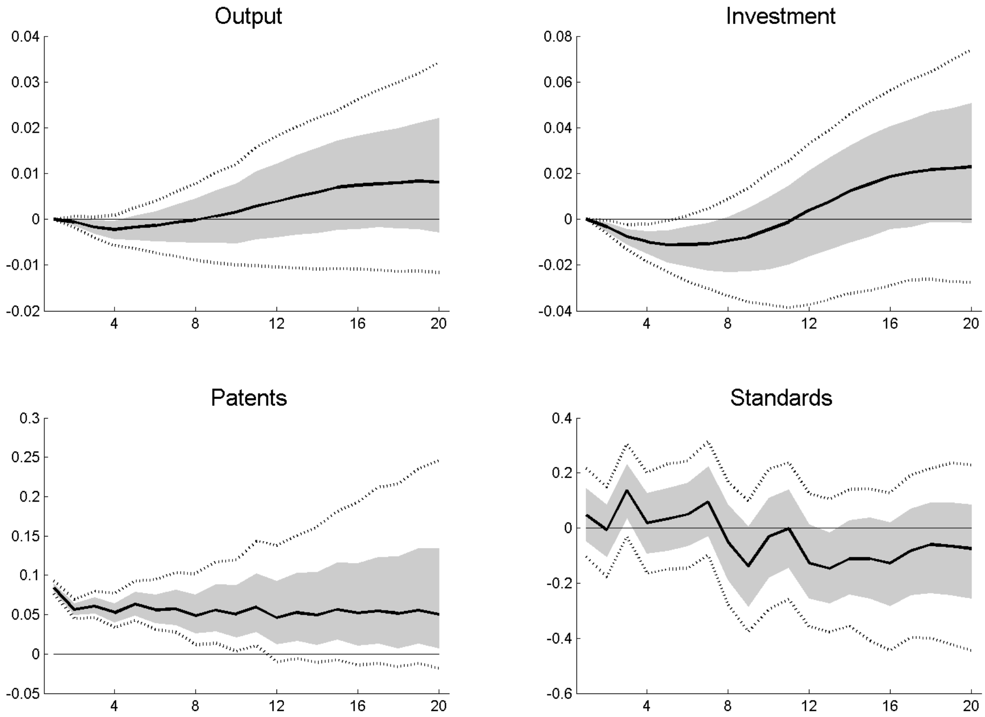
Notes: The historical decomposition refers to the VAR whose impulse response are displayed in figures 6 and 8. Data are HP-detrended. Standard data are averaged over a centered window of 5 quarters.

Figure 11: IRFs: Standards signalling news

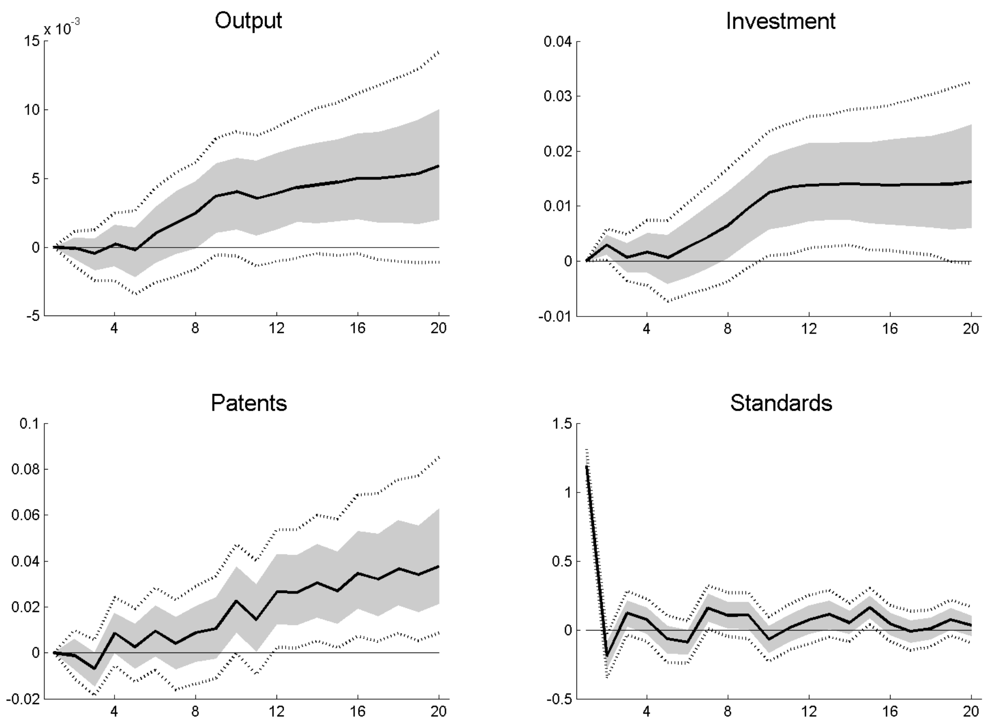


Notes: Impulse responses to a one standard deviation shock to standards. The ordering is: output, investment, TFP, ICT standards and the stock market index. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively.

Figure 12: IRFs: Patent-standard dynamics



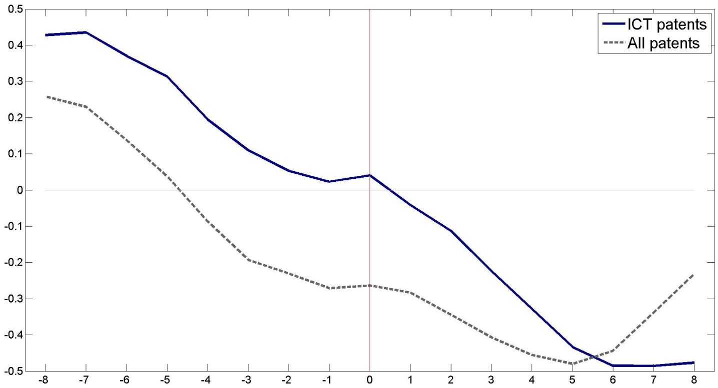
(a) Patent shocks



(b) Standard shocks

Notes: Impulse responses to a one standard deviation shock to patents. The ordering is: output, investment, ICT patents and ICT standards. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively.

Figure 13: Cross-correlations of originality indices and patenting



Notes: Cross-correlations were calculated based on the data from 1980Q4 to 1999Q2. The data were smoothed by using four quarter moving averages and the data peak of patent applications in 1995Q2 due to legal changes in US patenting law was corrected for by interpolating the data for 1995Q2-Q3.

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