# Technological Standardization, Endogenous Productivity and Transitory Dynamics

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Technological standardization is an essential prerequisite for the implementation of new technologies: The interdependencies of these technologies require common rules ("standardization") to ensure compatibility. Though standardization is omnipresent in industrialized economies, its macroeconomic implications have not been analyzed so far. Using data on standardization, we are able to measure the macroeconomic effects of the adoption of new technologies. *First*, our results show that new technologies diffuse slowly. Total factor productivity decreases temporarily, implying that the newly adopted technology is incompatible with the incumbent technology. *Second*, standardization reveals information about future productivity as evidenced by the positive and immediate reaction of stock market variables.

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# 1 Introduction

Standardization is a crucial and pervasive feature of industrialized societies. Entire industries coordinate the introduction and adoption of new technologies through the development of technology standards. However, the literature has so far overlooked the important role of standardization for technology adoption and macroeconomic variables.[1]

In this paper, we exploit the fact that standardization is at the heart of the adoption of Information and Communication Technologies (ICT) for the identification of economy-wide technology shocks. We quantify the impact of standardization on the business cycle and demonstrate its importance for macroeconomic dynamics.

Standards shape many objects of our daily life. Prominent examples of standards include electricity plug standards, paper size formats or quality standards (e.g. ISO 9001:2008). Standardization is particularly crucial for the adoption of ICT. Many ICT are subject to strict *compatibility requirements*: different technological applications have to be based on common standards in order to benefit from the network effects that are generated by the wide-spread use of interoperable technologies (Katz and Shapiro, 1985).

Standardization is thus a prerequisite for the implementation of ICT technologies. The development of the Internet was made possible by the definition of Internet protocols and other universal communication standards. Technological progress in wireless telecommunication proceeded through the development of various generations of standard families (1G, 2G, 3G, 4G and now 5G telecommunication standards). These technologies affect the production processes of a large number of sectors and have therefore been labeled a General Purpose Technology (GPT).[2] Due to their economy-wide use, the underlying standardization process in ICT generates technology shocks that can be expected to have aggregate macroeconomic effects.

[1]To our knowledge, there is only one other paper that treats the concept of "standardization" in a macroeconomic setting, but it differs conceptually from our use of the term "standardization". In Acemoglu *et al.* (2012), standardization is the process through which the tasks associated with a new technology become more widely and routinely practiced. Therefore, standardization is modeled as the process of turning an existing high-tech product into a low-tech one. In contrast, the concept of standardization in this paper specifically refers to *technology standards* developed by standard-setting organizations (SSOs) to ensure the interoperability of devices and/or technologies.

[2]Earlier examples of GPTs are the steam engine, railroads or electricity. Gross (2019) shows that the standardization of railroad gauges in 1886 in the South of the US resulted in a sharp increase in railroad shipments: the increase of 50% was in large part a substitution away from steamship traffic.

Our findings can be summarized as follows. 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 8% of business cycle fluctuations and 29% of fluctuations at lower frequencies. Following a technology shock, investment in information processing equipment and software picks up across all sectors and does so to a larger degree than other types of investment. In the short run, standardization produces important transitory dynamics. The reaction of output and investment to our technology shock is S-shaped, thus implying slow diffusion. Moreover, we find that TFP decreases in the short-run. We interpret this finding as an indication of the incompatibility of the new standard with the incumbent technology. When we use information on whether a standard is genuinely new or just an upgrade of an already existing standard (discontinuous vs. continuous technological change), we confirm that the temporary slump in TFP arises from discontinuous technological change.

We also find that the identified technology shocks communicate information to economic agents about future productivity in the spirit of Beaudry and Portier (2006): Stock market indices rise on impact to the identified technology shock. We confirm this finding both in a VAR framework with quarterly data as well as using daily stock market data around specific standardization events.

We make several contributions to the literature. First, we propose the use of standards as an important but overlooked indicator of technological change. While the literature has sometimes used patent counts to study the role of technological innovation for macroeconomic fluctuations, standard counts are a more compelling indicator of technology adoption. Standards – similar to patents – are clearly identified documents which describe detailed features of a technology. While many patented inventions are never or only rarely used, standards reflect the consensus of entire industries to adopt a technology. We make the standard series available in the online appendix and also provide the underlying code to extract standard counts for different technological fields to encourage other researchers to use these data.

Second, standardization is not only a direct indicator of technology adoption, but also *explains* fluctuations in the rate of technological progress and technology adoption. In the literature on the role of technology shocks in the business cycle, these shocks are often exogenously given and could be attributed to a variety of different causal mechanisms. By contrast, this paper aims to shed light on how the necessity to standardize leads to the industry-wide adoption of bundles of technologies and thus generates fluctuations in the rate of technological change.

Third, this paper also contributes to the literature by introducing a flexible, data-driven way to tackle *non-fundamentalness* (Lippi and Reichlin, 1993; Leeper *et al.*, 2013). Technology is endogenous to the economic cycle. To take into account these interactions, we use a vector autoregression (VAR) model for the empirical analysis. However, recovering structural shocks in the context of slow technology diffusion can prove difficult. We specifically adapt our VAR model to the context of slow technology diffusion by opting for a generous lag length and variable-specific shrinkage to capture the importance of distant technology lags for the dynamics of the system. We introduce this feature into macroeconometric modeling by using Bayesian techniques.

Finally, this paper also contributes to the recent literature on news shocks (Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009) by proposing an explicit example of a mechanism which reveals information about future macroeconomic developments and generates an immediate reaction of forward-looking variables.

**Related literature.** This paper is related to the literature on the effects of technology shocks on business cycles. Most of the empirical research in this field deduce technology shocks from macroeconomic data (King *et al.*, 1991; Galí, 1999; Basu *et al.*, 2006; Fernald, 2012). These approaches are highly dependent on their underlying identification assumptions. As an alternative approach, one can employ direct measures of technological change. On one hand, several studies rely on R&D and patent data to capture direct indicators of *inventive* activity (Shea, 1999; Kogan *et al.*, 2017; Akcigit and Kerr, 2018). Recently, this approach has been extended to identify technological news shocks (Miranda-Agrippino *et al.*, 2019; Cascaldi-Garcia and Vukotic, 2019). 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. Alexopoulos (2011) relies on technology publications, i.e. manuals and user guides, as a measure for technology adoption. 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. Standardization occurs prior to the actual use of new technologies, which is picked up by the indicator in Alexopoulos (2011). While the publication of technology manuals is a symptom of technology implementation, we propose to analyze standardization as a mechanism that *causes* coordinated implementation and contributes to explain fluctuations in the rates of technological progress and technology adoption.

This paper also relates to 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 (Greenwood *et al.*, 2000; Fisher, 2006; Justiniano *et al.*, 2010). However, compared to IST shocks, standardization takes place before the actual increase in the efficiency of new investment goods.

The vintage capital literature, in particular, has concentrated on the role of new technological vintages for macroeconomic dynamics (see for example Cooley *et al.*, 1997). This literature shows that productivity can slow down temporarily if the new technology requires learning and reorganization (Hornstein and Krusell, 1996; Greenwood and Yorukoglu, 1997; Yorukoglu, 1998). We argue that, following standardization, new products and processes are brought to the market during a lengthy implementation process ("time to implement", see Hairault *et al.*, 1997).

Our results show that stock markets nevertheless react positively on impact to the identified technology shock. We relate this finding to the high information content of standardization events. The fact that forward-looking variables react contemporaneously resembles the dynamics uncovered in the news shock literature (Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009; Barsky and Sims, 2011). Related to this literature, several papers use direct measures of technology to identify news shocks in VAR settings (Miranda-Agrippino *et al.*, 2019; Cascaldi-Garcia and Vukotic, 2019); Kurmann and Sims (2017) use our standardization indicator and show that it conveys news to economic agents.

The next section motivates and discusses the relevance of standardization using the example of mobile telecommunications. 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.

## 2 The role of standardization in technological innovation

### 2.1 Background: The standard-setting process

ICT is a General Purpose Technology (GPT, see Basu and Fernald, 2008; Jovanovic and Rousseau, 2005) and has constituted *the* dominant source of technological progress in many sectors of the economy in recent decades. Technological innovation in ICT is characterized by the requirement to achieve interoperability between different devices and between different technological inventions. This interoperability is achieved through standardization.

The prominent role of standardization for innovation in ICT has far-reaching implications for the macroeconomic analysis of technological change. In particular, standardization can explain why technological innovation may cause aggregate macroeconomic fluctuations. First, through standardization, many complementary inventions are developed together and are made simultaneously available. This translates into discrete discontinuous technological jumps. Second, entire industries coordinate on the adoption of these new technologies. This coordinated and simultaneous deployment of bundles of technologies represents a major macroeconomic event.

On one hand, through standardization, groups of firms or entire industries coordinate their efforts towards the *development* of a technology to be commonly used (Lerner and Tirole, 2015; Spulber, 2018). There are several ways to achieve this coordination, notably through voluntary participation in Standard-Setting Organizations (SSOs), as well as *de facto* standardization. Many important ICT standards are set by SSOs. Relevant examples of SSOs developing ICT standards are the Institute of Electrical and Electronics Engineers (IEEE) or the 3rd Generation Partnership Project (3GPP), a consortium of seven SSOs that cooperate in the development of technical specifications.[3]

Most SSOs are private organizations that develop technology standards through the voluntary contributions of their members. SSO membership is typically open to all interested stakeholders, and many SSOs have a broad membership base, including all relevant stakeholders from a particular industry.[4] Within SSOs, technical committees and working groups of industry representatives develop draft standards. Many SSO standards thus draw on the combined technical contributions of all of the most relevant firms in a particular industry.

On the other hand, technology standards coordinate the industry-wide *adoption* of new technologies. The application of technology standards developed by SSOs is voluntary, unless a standard is incorporated into binding government regulation.[5] However, using a standard is often necessary for companies in order to participate in a particular industry.[6] Furthermore, SSOs typically make decisions on the adoption

[3]See Baron and Gupta (2018) for a detailed analysis of the standardization process in 3GPP, and a description of the data on 3GPP specifications used in this section.

[4]In a sample of 200 SSOs operating in ICT, Baron and Spulber (2018) find that the median SSO has more than 100 member companies.

[5]SSOs can develop regulatory standards upon request of governmental authorities. Alternatively, voluntary SSO standards can be incorporated by reference into binding regulations.

[6]For example, the International Telecommunications Union (ITU-T) states: “Recommendations are standards that define how telecommunication networks operate and interwork. ITU-T Rec-

of a new standard by consensus. An SSO standard thus represents a wide agreement among a significant group of industry members on the most appropriate technological solution for a specific need.

### 2.2 An illustrative example

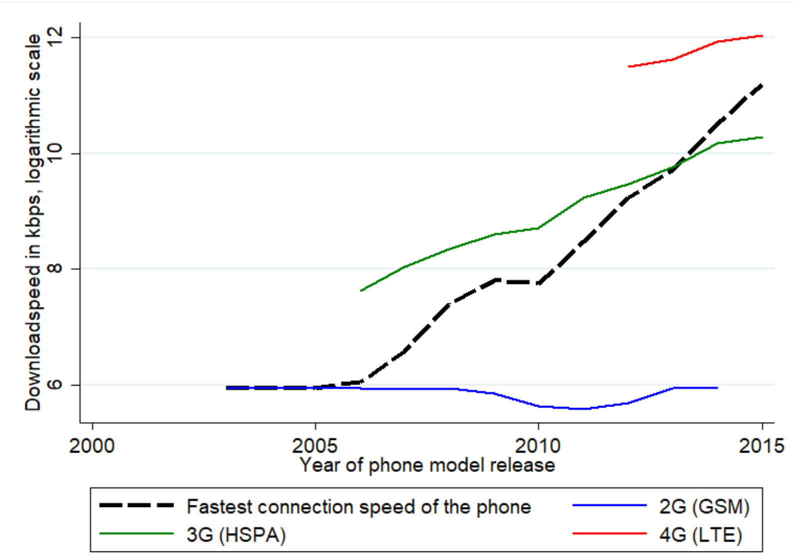
We will illustrate these implications using the example of mobile telecommunication technologies, and the role of the standards developed by 3GPP. Mobile telecommunication technology is one of the most visible and significant areas of technological progress over the last 25 years. Standardization in this industry enabled important technological advances: the average connection speed of new mobile telecommunication devices has dramatically increased, enabling the large number of applications for which contemporary smart phones are used. This process features several waves of significant technological improvements embodied in the different *generations* of mobile telecommunications standards.

**Discontinuous technological progress through standardization.** Figure 1 plots the evolution of the average connection speed of new phone devices introduced between 2003 and 2015, depicting a more than 600-fold increase. The average connection speed of new devices increases by an average of 90% per year over 2005–15. Most of this increase can be attributed to the introduction of new *generations* of mobile telecommunication technology. Second Generation (2G) technology such as GSM was first supplanted by Third Generation (3G) technologies such as UMTS and HSPA (green line in figure 1), and later by the Fourth Generation (4G) technology LTE (red line in figure 1), with each new generation marking a discrete technological jump.

3G, 4G, or 5G refer to a generation of inter-related standard specifications rather than a single technology. Each generation of phone standards incorporates thousands of interdependent inventions, reflected in the many thousand patents declared to be essential to these technology standards: close to 10,000 patents were declared to be essential to the 2G technology GSM, while 40,000 and over 45,000 patents, respectively, were declared essential for UMTS (3G) and LTE (4G) standards

ommendations are non-binding, however they are generally complied with due to their high quality and because they guarantee the interconnectivity of networks and enable telecommunication services to be provided on a worldwide scale." Cited from http://www.itu.int/en/ITU-T/publications/Pages/default.aspx

Figure 1: Exponential increase in connection speed of new phones




*Notes*: The figure plots the average download speed of different communication standards, by year of phone release. The figure is based on data on connection speeds of 4,026 different devices, introduced from 2003 to 2015. A single phone may be able to communicate using different communication technologies. The blue, green and red lines respectively plot the average download speed of mobile phones when using 2G, 3G and 4G technology. The dotted line represents the average download speed of each phone's fastest telecommunication technology. This average speed increases because of the technological improvements within each generation, and because of the increasing share of phones able to communicate using the most recent generation. We collected the data from *GSM Arena*, www.gsmarena.com.

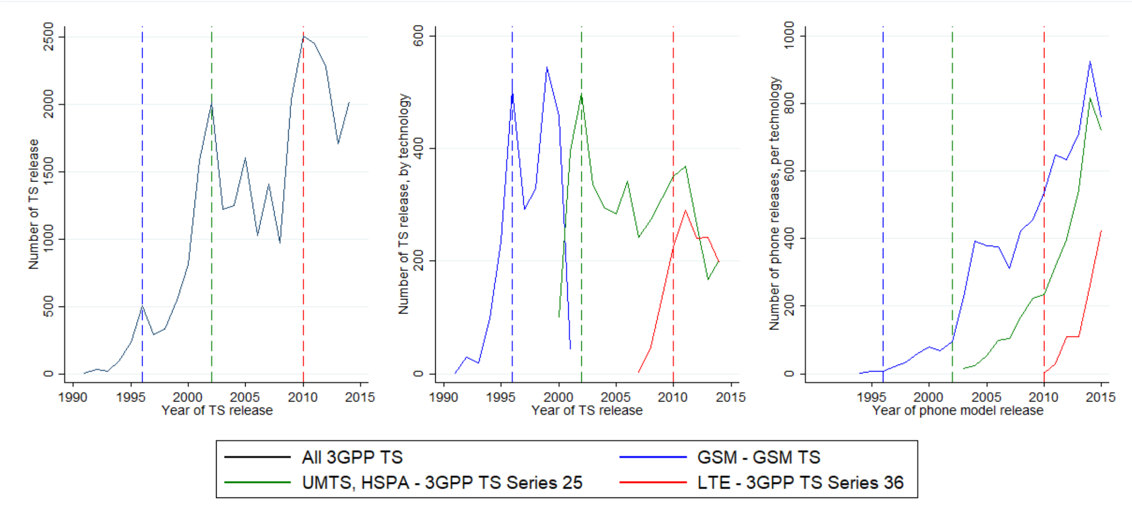
(Baron and Pohlmann, 2018).[7] The standardization process thus aggregates large numbers of individual inventions into a complex technological system. Individual technical specifications may already aggregate large numbers of individual technical contributions [8]. Furthermore, hundreds of such standard specifications are bundled together in one "generation" to describe complex technological systems such as GSM or LTE. With the release of a standard generation, many thousand inventions are thus simultaneously made available for implementation. Technology *shocks* rather than smooth technological progress result from this process.

[7]65 different companies declared to own 45,279 patents related to 11,604 different inventions that they believed to be *essential* to the LTE technology standard, 63 companies declared that they owned a total of 39,748 essential patents for the UMTS standard (relating to 9,390 different inventions), and 54 different companies declared to own a total of 9,868 essential patents (2,236 different inventions) for the GSM standard (Baron and Pohlmann, 2018).

[8]The technical specification TS 24.229 for example is a standard specification developed through more than 11,000 different written contributions from different 3GPP members (Baron, 2018; Baron and Gupta, 2018).

**Industry-wide technology adoption through standardization.** In addition to coordinating inventions and causing a discontinuous pattern of technological progress, standardization constitutes an explicit mechanism for technology selection and coordination on technology adoption.[9] By resolving technological uncertainty, standardization triggers the industry-wide implementation of new technologies.[10]

Figure 2: Standardization and diffusion of successive standard generations




*Notes*: The first panel plots the overall number of technical specifications (TS) released by 3GPP (and its predecessor organization GSM, whose activities were eventually merged into 3GPP). The second panel plots the technical specifications (TS) that can be attributed to each of the three generations of mobile telecommunications standards: blue (2G), green (3G) and red (4G). The third panel plots the number of phone models which incorporate the respective 2G, 3G and 4G technology. Data source: 3GPP and GSM Arena.

Using the mobile telecommunications technologies 2G, 3G and 4G as an example, figure 2 provides an example of the temporal coincidence between standard releases and the first stage of the mass introduction of new technologies. The two left-hand graphs in figure 2 depict the evolution of the count of new standard documents, called technical specifications (TS) in 3GPP.[11] The first graph displays the overall count, highlighting that there were several spikes over time. The second graph focuses only on those TS releases that can most immediately be attributed to one of the three generations: one can see three different "waves" of releases corresponding to the three

[9]Lerner and Tirole (2015) and Spulber (2018) analyze the standard setting process as a coordinated selection mechanism. In line with this theoretical analysis, Rysman and Simcoe (2008) empirically find that SSOs are generally efficient at selecting superior technologies.

[10]Aggarwal *et al.* (2011) analyze the role of standardization for reducing uncertainty inherent to technology development.

[11]3GPP develops technical specifications that are then transposed into standards by the regional member SSOs of 3GPP.

different generations. Each spike in the total series corresponds to one of the three waves that define a standard generation.

The right-hand graph in figure 2 tracks the implementation of the different generations of 3GPP standards in a sample of 7,658 telecommunication devices by plotting the number of phone models that incorporate the respective 2G, 3G or 4G technology.[12] We can see a succession of three diffusion curves, where each new communication technology is initially only implemented in a limited number of new devices, before implementation becomes more generalized. The three spikes in the number of standards releases correspond quite closely to the respective start of these three different diffusion processes.

Standardization is thus associated with the point in time when a new technology becomes available for implementation. This implementation begins with the release of the standard; the technology then gradually diffuses to a larger number of devices. There is thus a significant 'time to implement" (Hairault *et al.*, 1997), as firms need to develop new standard-compliant products or services or to adapt existing production structures to discontinuous technological change.

### 2.3 Aggregate standard counts and macroeconomic implications

**Individual technologies and the lumpiness of aggregate standard counts.** We have shown how standardization causes individual technologies such as mobile telecommunications to progress through a succession of discrete leaps. Next, we will show that such leaps in individual technological fields are sufficiently significant to cause spikes in aggregate ICT standardization activity. We therefore now turn to all technologies categorized as ICT and investigate the properties of aggregate standard counts.

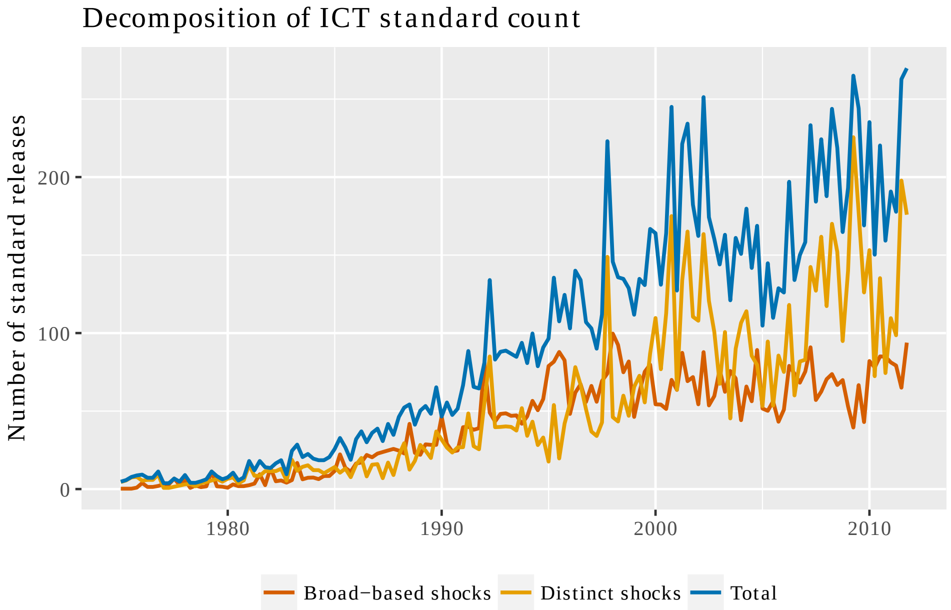
We use data from the Searle Center database on technology standards and standard setting organizations (Baron and Spulber, 2018) and construct time series by counting the number of standards which are released per quarter.[13] The International Classification of Standards (ICS) system allows assigning each standard to a specific technological field. We restrict the analysis to standards released in the ICS categories 33 (Telecommunications. Audio and video engineering.) and

[12] As in figure 1, the sample is drawn from the website GSM Arena (www.gsmarena.com). The sample for this analysis is larger and the observation period is longer because information on the phone's telecommunication technologies is more often available than information on connection speeds.

[13] See section 3 for further information. More information on the construction of the data can also be found in appendix G.

35 (Information technology.), as well as standards set by SSOs with an exclusive technological focus on individual ICT. The blue line in figure 3 plots the standard count for ICT standards released by US SSOs. One can observe a constant increase in the 1980s and 1990s. However, there is also a large amount of variability in the data and one notes the apparent lumpiness of the aggregate time series count.

Figure 3: Standard series 1975Q1–2011Q4




*Notes*: The series display the number of new standard releases per quarter ("standard count"). The left-hand side y-axis corresponds to ICT standards and the right-hand side y-axis corresponds to the total number of standards across all ICS classes which were released by US standard setting organizations over the period 1975Q1–2011Q4. The blue line plots the total count of ICT standard releases over the period 1975–2011. The overall count is broken down in those standards that were released in a given quarter in a 5-digit ICS class whose normalized share of the overall count in that quarter is 20% or more ("distinct shocks": yellow line) and the remaining standards ("broad-based shocks": orange line).

The spiky nature suggests that there are indeed "shocks", but do these shocks represent the arrival of distinct technologies (i.e. are these shocks driven by specific ICS classes) or do we see a co-movement across the subcategories contained in ICS 33 and 35? These subcategories are 5-digit ICS classes such as Integrated Services Digital Network (ISDN) [33.080], Microprocessor systems [35.160] or Data storage devices [35.220]. We decompose our aggregate series into two components, which we respectively label "broad-based" and "distinct" shocks, similar to the decomposition of aggregate investment in Gourio and Kashyap (2007). The series labelled "distinct shocks" counts the number of standards that were released in a given quarter in a 5-digit ICS class whose normalized share of the overall count in that quarter is

20% or more.[14] It thus counts technology shocks that can be traced back to an idiosyncratic increase in a specific technology (5-digit ICS class). The series labeled "broad-based shocks" picks up the remaining standards, thus tracking variations that affect many technologies.

Figure 3 shows that the variation in the aggregate series, and notably its spikes, are driven to a large extent by distinct, technology-specific variations. This analysis reveals that idiosyncratic technology shocks in individual technological fields lead to the spikes that characterizes the aggregate ICT standardization series.

**Economy-wide technology adoption.** In section 2.2, we highlighted that spikes in mobile telecommunications standardization coincided with the beginning of the diffusion of new telecommunication technologies in the product market. We also established that such idiosyncratic standardization shocks in individual technological fields translate into spikes in the aggregate ICT standardization series. We will now analyze whether spikes in aggregate ICT standardization are accompanied by an industry-wide increase in ICT adoption.

In order to address this question, we carry out an empirical exercise similar to Rajan and Zingales (1998). In particular, we regress investment rates in equipment per industry (our measure of aggregate adoption activity) on lagged counts of ICT standard releases, interacted with an indicator of the industry's dependence on ICT. If ICT standardization triggers the economy-wide diffusion of new ICT, we would expect that industries that use ICT to a large extent respond to ICT standardization with an increased rate of investment.

In particular, we follow Gutiérrez and Philippon (2017) and define the investment rate as current investment in industry $j$ scaled by last period's capital stock.[15] For our measure of ICT dependence we rely on the BEA's input-output tables. Dependence on ICT inputs is defined as the share of a sector's inputs from the following sectors in overall inputs: (1) Computer and electronic products [NAICS 334], (2) Publishing industries, except internet (includes software) [NAICS 511], (3) Broadcasting and telecommunications [NAICS 513], (4) Data processing, internet publishing, and other information services [NAICS 514] and (5) Computer systems design and related

[14] The share is normalized as it is calculated on the basis of a standard count that is weighted by the inverse of the mean number of standards per 5-digit ICS in order to take into account that certain ICS classes are by definition larger than others.

[15] Data are taken from the BEA's Fixed Assets accounts; the investment rate is the ratio of investment in private fixed assets over the current-cost net stock of private fixed assets.

services [NAICS 5415]. In total, we cover 61 industries, which are listed in the appendix. All data are annual.

All independent variables are included as lags in order to address endogeneity concerns. As we are interested in dynamic effects we include up to 5 lags ($L = 5$) of the variable of interest. In particular, the regression specification takes the form:

$$\frac{I_{j,t}}{K_{j,t-1}} = \alpha d_{j,t-L-1} + \sum_{l=1}^{L} \beta_l \Delta s_{t-l} d_{j,t-L-1} + f_t + f_j + \varepsilon_{j,t}$$

where $d_{j,t-L-1}$ is the average dependence of sector $j$ on ICT inputs in the ten preceeding years, i.e.

$$d_{j,t-L-1} = \frac{1}{10} \sum_{n=1}^{10} \mathrm{dep}_{j,t-L-n}$$

$\Delta s_{t-l}$ is the log change in the number of newly released ICT standards in $t - l$. We include both industry and time fixed effects.

Results are displayed in table 1. In column (1), results are displayed for total investment whereas columns (2), (3) and (4) decompose total investment respectively into equipment, intellectual property (which includes software, research and development (R&D), and entertainment, literary, and artistic originals) as well as structures.

The results in table 1 show that standardization induces a positive and significant reaction of investment in equipment. We interpret this increase as evidence for a pick-up in adoption activity at the aggregate level. As in the case of mobile phones, the pick-up is not immediate: it takes two years for investment in equipment to react significantly to a pick-up in standardization and this reaction is lasting for a couple of years.

Reassuringly, we find that this effect is limited to investment in new equipment. Investment in structures or intellectual property do not respond significantly to an ICT standardization shock.[16] At the bottom of table 1, we report the F-statistic of the joint significance of all the coefficients $\beta_l$; these are jointly significant for equipment investment only. ICT standardization thus leads to an investment response in a large number of industries using ICT as an input, but this response is limited to

[16] We expect that ICT standardization significantly interacts with investment in Intellectual Property within the industries that *develop* rather than *use* ICT.

Table 1: Regression results: Industry-level investment rates

| | (1) Total | (2) Equipment | (3) IP | (4) Structures |
|---|---|---|---|---|
| Dep. (t-6) | -0.00114 | -0.00032 | -0.00065 | 0.00001 |
| | [0.355] | [0.490] | [0.465] | [0.985] |
| Dep. (t-6) × Standards (t-1) | 0.00028 | 0.00051* | -0.00057 | 0.00025 |
| | [0.702] | [0.067] | [0.157] | [0.214] |
| Dep. (t-6) × Standards (t-2) | 0.00035 | 0.00078*** | -0.00054 | 0.00033 |
| | [0.588] | [0.000] | [0.261] | [0.122] |
| Dep. (t-6) × Standards (t-3) | 0.00060 | 0.00082*** | -0.00075 | 0.00030 |
| | [0.195] | [0.001] | [0.141] | [0.259] |
| Dep. (t-6) × Standards (t-4) | 0.00013 | 0.00065*** | -0.00091* | -0.00001 |
| | [0.740] | [0.005] | [0.068] | [0.973] |
| Dep. (t-6) × Standards (t-5) | -0.00026 | 0.00040** | -0.00081* | -0.00002 |
| | [0.611] | [0.027] | [0.089] | [0.921] |
| F-stat | 0.001 | 0.003*** | -0.004 | 0.001 |
| | [0.661] | [0.001] | [0.121] | [0.466] |
| Observations | 1631 | 1631 | 1631 | 1631 |
| $R^2$ | 0.81 | 0.81 | 0.89 | 0.67 |
| Adjusted $R^2$ | 0.80 | 0.80 | 0.89 | 0.65 |
| $j$-FE | Yes | Yes | Yes | Yes |
| $t$-FE | Yes | Yes | Yes | Yes |

*Notes*: The table presents the regressions results for a regression of investment rates on the ICT dependency ratio (calculated in $t-6$) and its interaction with lagged ICT standard counts. P-values are displayed in brackets. The F-statistic tests for the joint significance of all the interaction terms.

investment in new equipment (which presumably includes the vast majority of ICT implementations).

### 2.4 Take-away

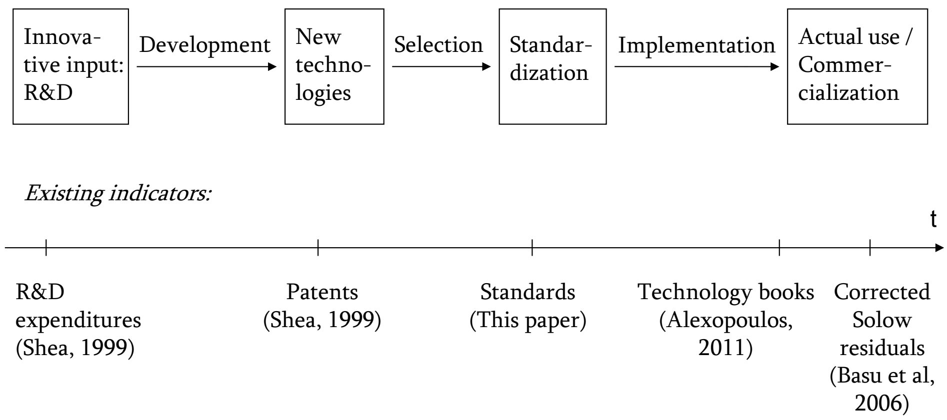
Our analysis of standardization contrasts with assumptions on technology adoption commonly used in macroeconomic models. These models usually assume that innovative activity is decentralized, with technological progress arriving stochastically. Such notions are inherent to the business cycle literature, as for example in Kydland and Prescott (1982) or Rotemberg (2003), but can also be found in macroeconomic models of innovation (Klette and Kortum, 2004; Acemoglu *et al.*, 2018). With regards to technology adoption, the macroeconomic literature usually considers this to be a firm-level decision, uncoupled from other firms' decisions (Jovanovic and MacDonald, 1994; Benhabib *et al.*, 2017).[17] By contrast, we have highlighted the importance of industry-wide coordination in both the development and the adoption

[17]Nevertheless, aggregate determinants such as knowledge spillovers and competitive pressure do matter, but direct coordination among firms is often excluded.

of new technologies. These coordination processes lead to discontinuous technological improvements, and clustered industry-wide adoption of complex bundles of inventions.

In the following econometric analysis, we will investigate the macroeconomic effects of this pattern of technology adoption. The schematic representation in figure 4 situates our analysis with respect to other studies of the role of technology for macroeconomic fluctuations. We argue that standardization is a crucial mechanism linking the invention of new technologies (as indicated e.g. by patenting) and their actual use and commercialization (as indicated e.g. by manuals and other indirect symptoms of technology adoption).

Figure 4: Stylized sequence of technological innovation and indicators




## 3 Description of the data

We employ data for the US economy. In order to retrieve time series on standardization, we use the Searle Center database on technology standards and standard setting organizations (Baron and Spulber, 2018).[18] This database includes standards set by more than 600 SSOs; including formal SSOs and more informal standards consortia (Chiao *et al.*, 2007). Our data do not cover *de facto* standards or the standards issued by ad hoc industry groups. An example of a *de facto* standard is the QWERTY keyboard. If a de facto standard or a standard developed by an ad hoc group gains wide acceptance, it is common that such standards are eventually

[18]The Searle Center database of technology standards and standard setting organizations is a database with comprehensive information on standards intended for academic research; for additional information, see http://www.law.northwestern.edu/research-faculty/searlecenter/innovationeconomics/data/technologystandards/index.html.

accredited as a standard by one of the formal SSOs in our sample.[19] Even though there are hundreds of SSOs 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 US standards.[20]

For many standards issued by large SSOs, the ICS classification allows assigning each standard to a specific technological field. In the case of smaller SSOs, the technological classification of the standard can generally be inferred from the technological focus of the issuing SSO. Table 2 shows that the database we are extracting for the period 1975Q1–2011Q4 contains a total of almost 640 000 standards of which roughly 16% 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 distribution of goods. More than 150, 000 standards are categorized as special technologies due to the fact that the Searle Center Database comprises "Military and Government Specs & Standards" from the Naval Publications and Form Center (NPFC) which we characterize as belonging to the ICS class 95 (Military engineering.).

Table 2: Characteristics by ICS classification 1975Q1–2011Q4

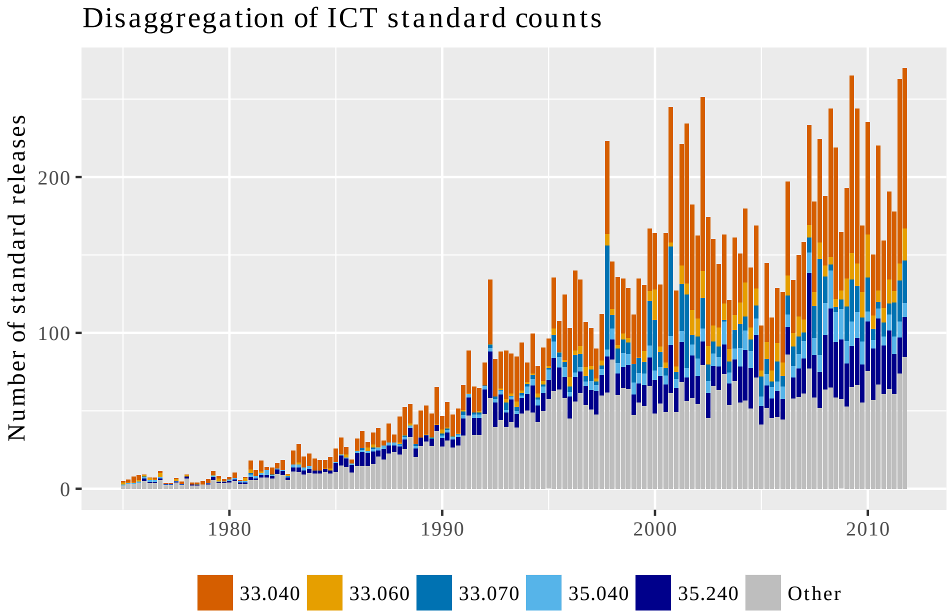
| | Number | | % new | |
|---|---|---|---|---|
| | US | US+Int | US | US+Int |
| Agriculture and food technologies | 3392 | 12254 | 59 | 62 |
| Construction | 14052 | 27568 | 40 | 44 |
| Engineering/electronics | 38151 | 87712 | 49 | 53 |
| Generalities, infrastructures and sciences | 14265 | 25902 | 61 | 59 |
| Health/safety/environment/agriculture/food | 13610 | 32596 | 49 | 50 |
| ICT | 17737 | 103954 | 74 | 65 |
| Materials technologies | 40398 | 65013 | 38 | 42 |
| Special technologies | 159275 | 166315 | 39 | 40 |
| Transport and distribution of goods | 55856 | 78563 | 64 | 63 |
| Not classified | 34458 | 39611 | 60 | 65 |
| Total | 391194 | 639488 | 48 | 52 |

*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. The number of total standards in the table does not equal the sum of the underlying ICS classes as standards can be categorized into more than one ICS class.

[19]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 released as an ISO standard.

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

Figure 5: Underlying technological fields in ICT standardization




*Notes*: All standards categorized in the ICS 2-digit classes 33 and 35 are broken down by ICS 5-digit categorization, in particular: 33.040 – Telecommunication systems, 33.060 – Radiocommunications, 33.070 – Mobile services, 35.040 – Information coding, and 35.240 – Applications of information technology. The category "Other" captures all remaining ICT standard classes. A standard can be classified into several ICS 5-digit classes which is why the above chart does not match the overall count in figure 3.

In most of the paper, we exclusively focus on ICT standards. While our database contains standards beyond the field of ICT (and electronics, which we include in a robustness analysis in section 6, we purposely limit our analysis to ICT. For one, the necessity to standardize is particularly pronounced in ICT as network externalities can only be realized when technologies are interoperable (Katz and Shapiro, 1985). Second, ICT are general purpose technologies (Basu and Fernald, 2008; Jovanovic and Rousseau, 2005) and can therefore be expected to have aggregate macroeconomic effects. ICT include a variety of distinct technological fields. Figure 3 decomposes our overall count from figure 5 into the underlying 5-digit ICS classes. The five most frequently appearing ICS classes are 33.040 (Telecommunication systems), 33.060 (Radiocommunications), 33.070 (Mobile services), 35.040 (Information coding) and 35.240 – Applications of information technology.

In addition, we are able to identify the national focus of the different SSOs. For the main analysis in this paper, we will use standards released by US-based SSOs, as these are the most relevant for the US economy. In the robustness section, we will show that our results hold when also including international SSOs whose standards also apply to the US ("US+Int").

In section 5.2, we distinguish between the effects of new and upgraded standards. We define a standard as *new* if it is the first standard in a version history; whereas the publication of a new version of an already existing standard constitutes an *upgrade* (Baron *et al.*, 2016). In section 6, we will also use certain standard characteristics (the number of pages or references) to assess the relevance of different standard documents. We obtain information on pages, references, and version histories from the Searle Center Database.

For a share of the standard counts, we only have information about the year, but not the month, of the release of the standard. We therefore adjust the 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.[21] In section 6.4, we will present robustness checks using annual data to show that results hold independently of the adjustment procedure. For details on the standards data, we refer to appendix G. We make the standard series available on the authors' websites where we also provide additional explanations and codes to extract standard counts.

Concerning macroeconomic variables, we will focus on the following series in the baseline version of the empirical model: output in the business sector, private fixed investment as well as total factor productivity (adjusted for capacity utilization) which is taken from John Fernald's website[22]. 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. All data are quarterly for the period 1975Q1–2011Q4. Detailed information on all the series, and in particular their sources, can be found in appendix F. For the estimations, all data series are in log levels.

## 4 Econometric strategy

We employ a vector autoregression (VAR) model in order to take into account that technology adoption could be partly endogenous to the cycle. The reduced-form

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

[22] See Fernald (2012) and http://www.johnfernald.net/TFP.

VAR system can be written as follows:

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

$X_t$ comprises the lagged variables of the VAR system and $A$ denotes the coefficient matrix. In the baseline version, $Y_t$ is composed of output in the business sector, private fixed investment, total factor productivity (adjusted for capacity utilization) as well as the standard count of ICT standards released by US SSOs.

Non-fundamentalness can arise in VARs with news shocks or slow technology diffusion: recovering structural shocks can be difficult if the space spanned by the shocks is larger than the space spanned by the data (Lippi and Reichlin, 1993; Leeper *et al.*, 2013). Appendix D provides a detailed 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. This is the approach taken in this paper: by including our standardization indicator into the VAR, we pick up the point in time when technology adoption is announced. However, we are also confronted with the fact that it takes time to adjust the newly standardized technologies to their final use – an issue that could reinstate non-fundamentalness. We therefore include 12 lags into the VAR, instead of the usual 4 lags often employed for quarterly data.[23]

A generous lag length, however, can cause problems due to overparameterization. We tackle this trade-off by using Bayesian shrinkage in a flexible, data-driven way. In particular, we allow for variable-specific lag decay to reduce parameter uncertainty while still fully exploiting the information contained in longer lags of the standard series. In order to implement this approach, we use a Normal-Wishart conjugate prior which assumes the following moments:

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

In particular, we impose a Minnesota prior, i.e. the first own lag of variable $i$ is equal to a certain value $\delta_i$ while all other prior coefficients are zero:

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

[23]Canova *et al.* (2010) also include 12 lags in order to avoid problems of non-fundamentalness. 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.

Macroeconomic variables such as output, investment or TFP are non-stationary due to the unit root properties of the time series (which are included into the VAR in log levels). The non-stationarity of the macroeconomic variables is taken care of by specifying $\delta_i$ accordingly. In particular, the prior coefficients for the macroeconomic variables mimic their unit root properties ($\delta_i = 1$) and the one for standardization assumes a white noise behavior ($\delta_i = 0$). Thus, we explicitly model the fact that output, investment and TFP have a unit root, while this is not the case for the standard series.

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, thus reducing parameter uncertainty ("Bayesian shrinkage"). The variance of the prior coefficients is set as follows:

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

The vector $\phi = (\phi_1\ \phi_2\ \phi_3\ \phi_4\ \psi_i)$ denotes the hyperparameters that govern the "tightness" of the prior. The prior on the constant is assumed to be uninformative ($\phi_3 = 10^6$). The Minnesota prior is Normal-Wishart and thus requires a symmetric treatment of all equations (Kadiyala and Karlsson, 1997; Sims and Zha, 1998), which is why $\phi_2 = 1$.[24] The parameter $\phi_1$ controls the overall shrinkage of the system.[25] $\psi_i$ are scale parameters.

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 uniformly across all variables. However, since the purpose of a generous lag length is to capture slow technology diffusion, we allow for variable-specific shrinkage of distant lags (via $\phi_{4,j}$) which we estimate from the data. By doing so, we want to avoid to forcefully shrink the influence of long lags of standards (or any other variable), but rather "let the data speak" on the amount of lag decay for each variable.

With $\phi_2$ and $\phi_3$ being fixed, we collect the remaining hyperparameters in the vector $\Theta = (\phi_1\ \phi_{4,j}\ \psi_i)$. In setting $\Theta$, we follow Canova (2007), Giannone *et al.* (2015) and Carriero *et al.* (2015) and maximize the marginal likelihood of the data,

[24] For the same reason, the same lag decay for each variable is imposed on all equations.

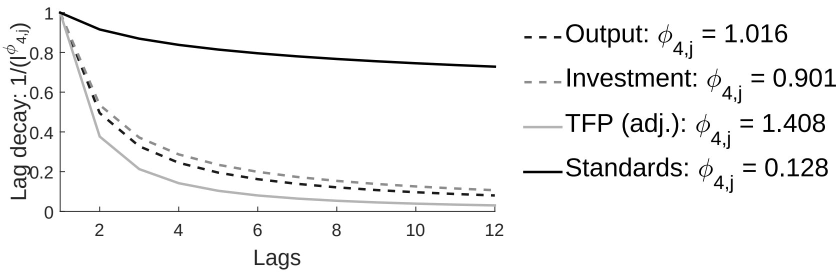
[25] When $\phi_1 = 0$, the posterior distribution tends towards the prior distribution; when $\phi_1 = \infty$, the prior is flat and the posterior estimates coincide with the ordinary least squares estimates.

$p(Y)$, with respect to $\Theta$:

$$\Theta^* = \arg\max_{\Theta} \ln p(Y) \quad \text{where} \quad p(Y) = \int\int p(Y \mid \alpha, \Sigma)\, p(\alpha \mid \Sigma)\, p(\Sigma)\, d\alpha\, d\Sigma$$

The maximization of $p(Y)$ also leads to the maximization of the posterior of the hyperparameters. The latter are therefore estimated from the data. Appendix B describes the prior distributions, the posterior simulation and the selection of the hyperparameters in more detail.

Figure 6: Lag decay estimates




*Notes*: The figure displays the estimates of the lag decay parameter and the implied shrinkage at different lags 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.

The comparison of the estimated lag decay is informative for evaluating the relevance of variable-specific Bayesian shrinkage. Figure 6 displays the implied lag decay (i.e. $1/l^{\phi_{4,j}}$ as a function of $l$) for the baseline model which includes output, investment, TFP and the standard series. The results 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 the inclusion of a generous lag length and variable-specific shrinkage in the first place.

## 5 Discussion of results

We use a recursive (Cholesky) identification scheme to recover the structural technology shocks from the reduced-form errors. The standard series is ordered last and the technology shock is recovered from its reduced-form innovations. Using this ordering, we therefore follow Shea (1999) and Alexopoulos (2011) who identify technology shocks from patent data and technology manuals respectively. Our identification approach is motivated by the literature on technology diffusion which has shown that new technologies diffuse slowly. We should therefore expect the emergence of a desirable technology to affect standardization on impact, but not output, investment or TFP. In addition, a Cholesky identification scheme imposes minimal assumptions on the model.[26] Nevertheless, we note that the ordering of the variables in the VAR with Cholesky identification does not have large consequences on the impulse responses. Ordering the standard series first leads to very similar impulse responses where macroeconomic variables on impact are statistically not significant from zero.

Figure 7 displays the impulse responses to the identified technology shock. 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: 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.

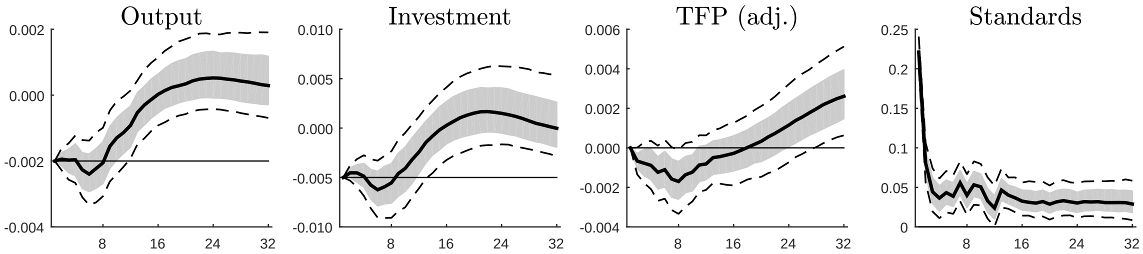
The primary interest of this paper is to investigate the aggregate effects of technology shocks on the macroeconomic cycle. We will first discuss the reaction of output and investment before turning to TFP further below.

### 5.1 The effect of technology shocks on output and investment

**Impulse responses.** The reaction of output and investment is positive and S-shaped. In particular, the reaction is sluggish immediately after the shock, picks up after 6 quarters and reaches its maximum after 16–24 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. The effects of the type of technology adoption we measure in our setup materialize fully after 4–6 years.

[26] 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.

Figure 7: IRFs – Responses to a technology shock




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

In an additional exercise, we explore which sub-components of investment are most affected. To this end, we estimate a VAR where the variable representing the respective type of investment is block-exogenous to the remaining VAR system.[27] Table 3 reports the responses of several subcomponents of private fixed investment to standardization, lagged by 16 quarters.

Table 3: Impact of a technology shock, IRF at horizon 16

| Investment series | |
|---|---|
| Equipment | 0.74* |
| Information processing equipment | 1.70** |
| Computers and periphal equipment | 3.93** |
| Other information processing equipment | 0.70** |
| Industrial equipment | 0.38 |
| Transportation equipment | 1.06* |
| Other equipment | 0.29 |
| Intellectual property products | 0.99** |
| Software | 1.97** |
| Research and development | 0.73** |
| Entertainment, literary, and artistic originals | 0.62** |

*Notes*: The table displays the value of the impulse response function to the identified technology shock for different investment types after 16 quarters (multiplied by 100). The identified technology shock is exactly the same as the one in the baseline model and its effect on the respective sub-component of investment is estimated by imposing block exogeneity. "*" and "**" respectively denote significance at the 16th/84th and 5th/95th percentile.

[27] In particular, the estimated VAR 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. Bayesian techniques are used as described in section 4. This block exogeneity assumption ensures that the estimated VAR coefficients of the main block remain the same as in the baseline model and that the technology shock is identified consistently across all investment components. Details on the implementation of the block exogeneity VAR and its Bayesian estimation can be found in appendix C.

The results corroborate our argument that the previously identified increase in investment is a causal economic response to an ICT-specific technological shock: the reaction of investment in computers and peripheral equipment exceeds the one of other types of equipment by one order of magnitude. The second largest reaction is the one by investment in software.

ICT standardization thus captures ICT-specific technology shocks, which translate into an ICT-specific investment response. This response is however not limited to specific sectors such as ICT-producing industries: computers and software are used as input factors in a large variety of sectors of the economy which is why aggregate ICT investment *across all sectors* picks up as shown in table 3.

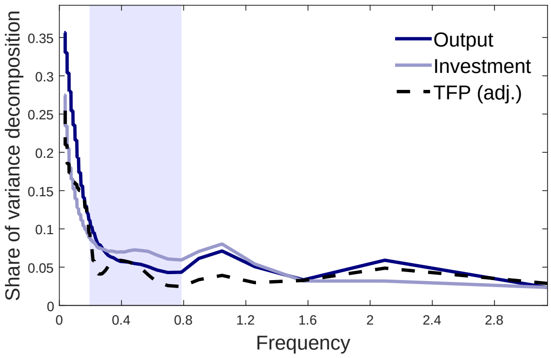
**Quantitative importance of technology shocks.** In order to analyze the relative importance of the identified technology shock, we rely on variance decompositions. In particular, we compute these variance decompositions in the frequency domain. Appendix A describes the computation of these decompositions. The results are displayed in the left panel of figure 8: the variance decomposition for the three macroeconomic variables in levels are plotted against the frequency (left to right, the axis extends from low frequencies, the long-run, to high frequencies, the short-run); the shaded region represents business-cycle frequencies. The right panel summarizes these results for very short-run (2–7 quarters), business cycle (8–32 quarters) and medium-term (33–200 quarters) frequencies.

Our results indicate that the identified technology shock is not the primary cause of macroeconomic fluctuations, but its contribution is still economically sizeable. From figure 8, it is obvious that technology shocks play a more important role for output, investment and TFP at lower frequencies. Between 19% and 29% 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 6% and 8%.

The fact that the response of output and investment to standardization is S-shaped (figure 7) is representative of slow diffusion. It is therefore unsurprising that standardization has a more significant effect at lower frequencies. As it takes time to adapt the newly adopted technology to its final use, macroeconomic variables are affected to a larger degree in the medium-run than in the short-run (see the right panel in figure 8). A similar point is also made in Jovanovic and Lach (1997) who link lengthy diffusion lags to the inability of the introduction of new products to generate output fluctuations at high frequencies.

Figure 8: Variance decompositions

(a) Graphical representation




(b) Summary table

| Frequency | 2–7 | 8–32 | 33–200 |
|---|---|---|---|
| Output | 0.06 | 0.08 | 0.29 |
| Investment | 0.06 | 0.08 | 0.19 |
| TFP (adj.) | 0.05 | 0.06 | 0.20 |
| Standards | 0.94 | 0.78 | 0.43 |

*Notes*: The variance decompositions refer to the VAR whose impulse responses are displayed in figure 7. The left panel displays 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 (33–200 quarters) whereas the ones greater than 0.8 correspond to high-frequency fluctuations (< 8 quarters). The right panel summarizes the contribution of the identified technology shock at business cycle frequencies (8–32 quarters) as well as over the medium- to long-run (33–200 quarters).

We present the variance decompositions in the frequency domain to better be able to compare business cycle and medium/long-term implications whereas most of the literature uses forecast error variance decompositions. Though not directly comparable, we find similar magnitudes for the variance decompositions as Alexopoulos (2011).[28] In some other studies, technology shock explains a significantly larger share of aggregate fluctuations.[29] These larger magnitudes largely reflect differences in scope, as many of these studies adopt an extremely broad notion of "technology shocks", which subsumes highly heterogeneous types of shocks to TFP. In this paper, by contrast, we identify a precisely defined technology shock. Other "technology shocks" such as policy changes, organizational 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

[28] Alexopoulos (2011) finds that technology shocks identified from technology publications account for a considerable portion of GDP fluctuations (i.e. about 10–20% after 3 years), with the contribution of technology shocks being more important at longer horizons.

[29] For example, Basu *et al.* (2006) find that shocks identified from Solow residuals which are corrected for non-technology factors account for 17% of GDP fluctuations after 1 year and 48% after 10 years. Using predominantly estimated structural models, the IST literature finds that the contribution of IST shocks to aggregate volatility ranges from about 20% to 60%. Greenwood *et al.* (2000) find that 30% of business cycle fluctuations can be attributed to IST shocks. A 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.

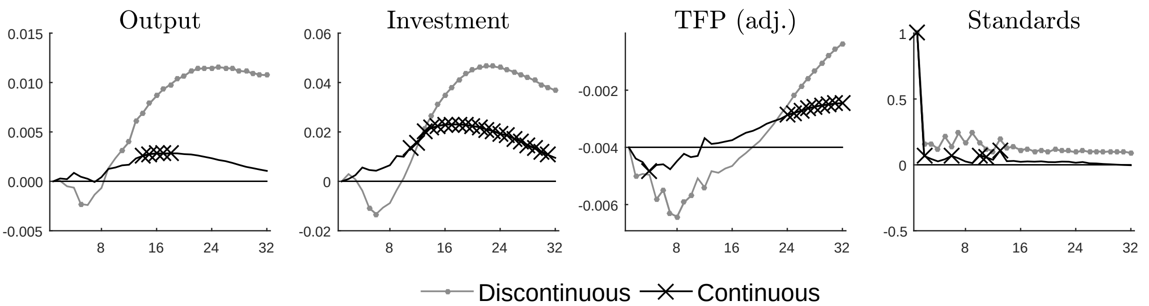
separately. Taking into account that we are isolating a specific technology shock, the measured contribution to aggregate volatility appears to be economically sizeable.

### 5.2 Effect of technology shocks on TFP

The impulse response of TFP to the identified technology shock measures to which extent the adoption of new technologies translates into higher productivity. Figure 7 shows that TFP decreases in the first quarters following a technology shock before picking up in the medium- and long-run.

We interpret the temporary decrease of TFP as evidence for the incompatibility between new and incumbent 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. In terms of compatibility across vintages, the effect of adopting a standard should depend on whether it is a genuinely 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 previously released standards from the standard count ("discontinuous") and one which only consists of upgraded versions ("continuous"). Both series measure technological change; however, we interpret the series of new standards as discontinuous technological change.

Figure 9: IRFs – Discontinuous vs. continuous technologies




*Notes*: Impulse responses to technology shocks identified from data on new standards (discontinuous) and upgraded (continuous) standard versions. Crosses and circles denote that the response is significant at the 16th/84th percentile. The unit of the x-axis is quarters.

Figure 9 displays the reaction to a technology shock deduced from the different standard measures. The shock is normalized to one for better comparison. The response of TFP is less pronounced for standard upgrades ("continuous"). New standards ("discontinuous"), however, induce a negative and significant reaction of TFP in the short-run and a large and significant increase in TFP in the long-run.

These findings provide further support for the interpretation that the slowdown in TFP is related to the fact that a new technology is incompatible with the incumbent one.

Differentiating between discontinuous and continuous technological change also helps to interpret the reaction of investment. In the case of continuous technological change, investment picks up in the short-run, suggesting that the new technology is rapidly integrated into production processes. On the contrary, for discontinuous technological change, we observe that investment actually drops in the short-run. One interpretation could be that there is considerable "time to implement" as existing production structures need to be adjusted to the new technology and the different applications of the new technology have to be developed. After sufficient time has elapsed during the implementation phase, investment picks up considerably.

Table 4: Variance decompositions – Discontinuous vs. continuous innovation

| | Discontinuous | | | Continuous | | |
|---|---|---|---|---|---|---|
| Frequency | 2–7 | 8–32 | 33–200 | 2–7 | 8–32 | 33–200 |
| Output | 0.06 | 0.09 | 0.30 | 0.03 | 0.02 | 0.05 |
| Investment | 0.06 | 0.10 | 0.20 | 0.03 | 0.03 | 0.08 |
| TFP (adj.) | 0.06 | 0.06 | 0.21 | 0.03 | 0.02 | 0.05 |
| Standards | 0.94 | 0.79 | 0.45 | 0.97 | 0.74 | 0.09 |

*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).

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 4. This holds true for both business cycle and medium- to long-run frequencies.

Our findings on the transitory effects of standardization run counter to models where technology shocks are assumed to lead to immediate increases in TFP. However, our evidence on the reaction of TFP is consistent with research in industrial organization and the vintage capital literature: 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) or workers' skill set (Chari and Hopenhayn, 1991). The vintage capital literature emphasizes the role of learning and reorganization for productivity dynamics following a technology shock (Hornstein and Krusell, 1996; Cooley *et al.*, 1997; Greenwood and Yorukoglu, 1997). TFP can therefore temporarily decrease, before the implementation and deployment of the new technology raises the level of productivity permanently as figure 7 shows.

Since we are concentrating on ICT standards, our results also relate to the so-called "productivity paradox", which addresses the discrepancy between low productivity growth and high rates of ICT deployment in the 1980s. As Robert Solow said in 1987: "You can see the computer age everywhere but in the productivity statistics". Yorukoglu (1998) finds that the introduction of ICT requires a considerable investment into learning. He specifically relates the incompatibility between different ICT vintages to differences in technological standardization in ICT. Samaniego (2006) stresses the need for reorganization at the plant level due to the incompatibility of new ICT technologies with existing expertise.

### 5.3 Technological change and financial markets' reaction

We explore whether stock market variables react to standardization events. This analysis is motivated by the findings in Beaudry and Portier (2006), who show that stock market variables can capture information about future macroeconomic developments. The previous section showed that the response of macroeconomic variables to the identified technology shock is sluggish. Despite the fact that aggregate responses only materialize after considerable delay, agents observe the initial shock (the standardization event). We therefore ask whether this information is picked up by stock markets. 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.

In Beaudry and Portier (2006), news about future productivity growth are associated with *positive* innovations in stock market variables. However, in the context of a technology shock as defined in this paper, the *sign* of the reaction of stock market variables is not straightforward. On the one hand, the value of existing capital decreases in response to the emergence of new technologies because the former will be replaced by the latter (Hobijn and Jovanovic, 2001). On the other hand, 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 due to technology adoption.[30] If the latter effect dominates, stock markets react positively (Comin *et al.*, 2009).

[30] For example, Pástor and Veronesi (2009) find that the large-scale adoption of new technologies leads to initial surges in stock prices of innovative firms.

**VAR analysis.** We therefore add the NASDAQ Composite and S&P 500 indices to the VAR. 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).[31] However, since we specifically focus on *technology* shocks, we also add a stock market index that captures developments in the field of technology as the NASDAQ does. They are ordered last as we assume that financial markets are by their very nature forward-looking – contrary to macroeconomic variables which do not react on impact due to implementation lags and slow diffusion. As before, we recover the technology shock from the innovation of the standard series. Based on the above results, we keep the identification that macroeconomic variables (output, investment, TFP) do not react on impact.[32] We therefore do not model a news shock: in contrast to an identification based on VAR innovations in stock prices (or TFP), our identified technology shock is orthogonal to those. Our identification assumption is based on slow diffusion (i.e. no contemporaneous impact on output, investment or TFP) which differs from an assumption aimed at identifying news shocks.

Results are displayed in figure 10 which, first of all, shows that the findings from the earlier exercise (i.e. figure 7) are not affected by the inclusion of financial market variables. The impulse responses in figure 10 show that both the S&P 500 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 on impact compared to the response of the more general S&P 500. The reaction of the S&P 500 and NASDAQ Composite indices confirm that financial markets pick up the information about future productivity increases despite the initial decline in TFP and the S-shaped response of output and investment.

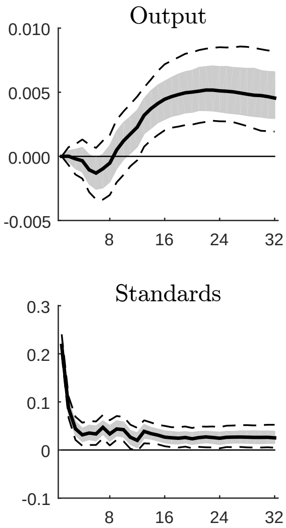
The identified shock explains a smaller share of aggregate volatility than typically found in the news shock literature.[33] As before, this is due to the fact that we are isolating a very specific shock, which comprises only a subset of the disturbances

[31] Kurmann and Mertens (2014) discuss the identification problems that arise when a VAR with first-differenced variables that includes more than TFP and stock prices is used in combination with the identification procedure of (Beaudry and Portier, 2006) who rely on long-run restriction and assumptions on cointegration relationships. Though we use a multivariate VAR, our identification is immune to this criticism as we are estimating the VAR in levels and rely on short-run restrictions.

[32] This is also motivated by alternative identification schemes where the standard series is ordered first and impulse responses of output, investment and TFP are not significant on impact.

[33] As above, we note that the variance decomposition in the frequency domain and conventional forecast error variance decompositions are not comparable. In Beaudry and Portier (2006) and Barsky and Sims (2011), news shocks account respectively for approximately 40–50% and 10–40% of output fluctuations at horizons of 1 to 10 years.

Figure 10: IRFs – Responses to a technology shock




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

that news shocks comprise (i.e. news about future productivity growth which are unrelated to technological change that is triggered by standardization).

**Analysis using daily stock market data.** We further investigate the relation between stock markets and standardization by using data at a higher frequency than usual macroeconomic VAR analysis permits. The goal of this exercise is to analyze the evolution of firms' share price around the decisions on standard releases. Such an event study approach, though not without its flaws, is informative about whether stock markets pick up the information contained in standard releases on impact.

We exploit available data on the dates of the plenary meetings of an important SSO, namely 3GPP. At the plenary meetings, representatives of all 3GPP member firms vote on fundamental technological decisions and the release of new standards.[34] Prior to the plenary meeting, there is considerable uncertainty regarding the outcome of the vote and the features of the future standard.

[34]Proposed technology standards, change requests and technical reports are drafted and discussed in more frequent meetings of smaller working groups. Important technological decisions are however taken at plenary meetings in an open vote.

We use data on 3GPP meeting dates and participants for the years 2005–2013. In total, 208 plenary meetings were held during that time.[35] We use meeting attendance data to identify the ten firms that sent the largest number of representatives to plenary and working group meetings[36] and collect daily data on their share prices (end-of-day). We extract the share price evolution of each of the ten firms five days prior and ten days following each meeting start date and normalize the series to unity one day prior to the start of the meeting. We also construct a second similar series for all non-meeting dates and calculate the mean over all non-meeting dates. We then subtract this second series from the share price series for each meeting date. The resulting series is thus normalized to zero one day before the start of the meeting. We do so in order to evaluate to what extent meeting dates generate stock price movements in excess of normal developments, therefore excluding that general trends over 2005–2013 influence the results.

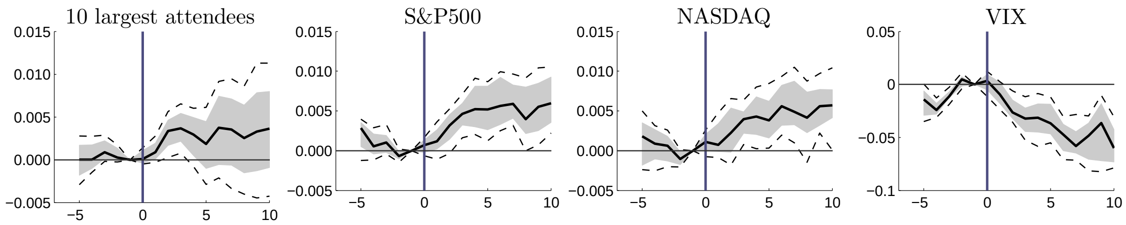
The plenary meetings at 3GPP last several days and comprise several announcements, which cannot be timed precisely. Compared to other event study analyses that investigate the impact of announcements, we therefore have to use a very large window. As a consequence, other events might occur within the same time frame. Since we are averaging over 208 meetings, we should *a priori* be able to eliminate these confounding events. However, the distribution of the stock market series around the meeting dates remains skewed, which is why we use the median over the 208 meetings to trace out the typical reaction of stock market variables to decisions at 3GPP plenary meetings.

The evolution of share prices before and after the start of a plenary meeting is depicted in figure 11. The vertical line marks the start of the meeting. Plenary meetings typically last three or four days. Figure 11 shows that the average share price fluctuates around its normalized value of zero prior to the meeting. With the onset of the meeting, however, share prices continuously rise. We replicate the analysis using the broader stock market indices NASDAQ and S&P 500. Both indices exhibit a positive response to 3GPP plenary meetings, which is very similar to the behavior of the share prices of the ten most involved 3GPP members. Six to seven days after the start of the meeting, stock prices have significantly increased by 0.3–0.5%. The transition after the start of the meeting is very smooth. Most likely, this

[35]Plenary meetings are held by Technical Specification Groups, TSGs, of which there are four different ones. As these meetings are often held in parallel, the bootstrapping of the confidence bands is obtained by clustering on the level of the grouped (parallel) dates.

[36]The results do not hinge on the number of firms we include. Results are similar for the top 20, 30, 40 or 50 participants.

Figure 11: Share prices and SSO meetings




*Notes*: The figure displays the median share price of the ten largest firms attending the SSO around the first day of the SSO meeting (vertical line at $x = 0$). The unit of the x-axis is (trading) days. The median is taken over firms' share prices and meeting dates. Share prices are normalized by the value of the price of each share one day prior to the start of the meeting and the mean evolution around non-meeting dates is subtracted from the series, resulting in a normalized value of zero. Confidence bands are obtained using bootstrapping. The black line represents the median, the corresponding shaded regions denote the 16th and 84th percentiles and dotted lines denote the 5th and 95th percentiles.

is due to the fact that meetings last between one and five days. Therefore, the effect of decisions at plenary meetings is not timed identically across all meetings. Overall, the reaction of financial market data shows that important standardization decisions, such as those made during the plenary meetings of 3GPP, disclose information that is relevant to the general economy.

Which forces could explain the overall positive reaction to meeting events despite the fact that a particular firm's preferred standard might not be chosen? In the latter case, it is likely that individual firms' share prices can also react negatively to a particular meeting. The overall positive reaction, however, can be explained by the resolution of uncertainty that the votes at plenary meetings bring about. If investment is irreversible, uncertainty is delaying firms' investment decisions (Bernanke, 1983; McDonald and Siegel, 1986; Pindyck, 1991; Bloom, 2009). A standard that has not yet been voted on will not generate any pick-up in investment as long as the uncertainty about its fate has not been resolved. In the same way, a vote to discard a standard reduces uncertainty and thus leads to a positive reaction by financial markets. We therefore trace out the evolution of the VIX, a measure of uncertainty in financial markets, around 3GPP meetings. As shown in figure 11, the VIX declines with the onset of the meeting and remains significantly below zero after the start of the meeting.

# 6 Extensions

## 6.1 Enlarging the definition of relevant standards

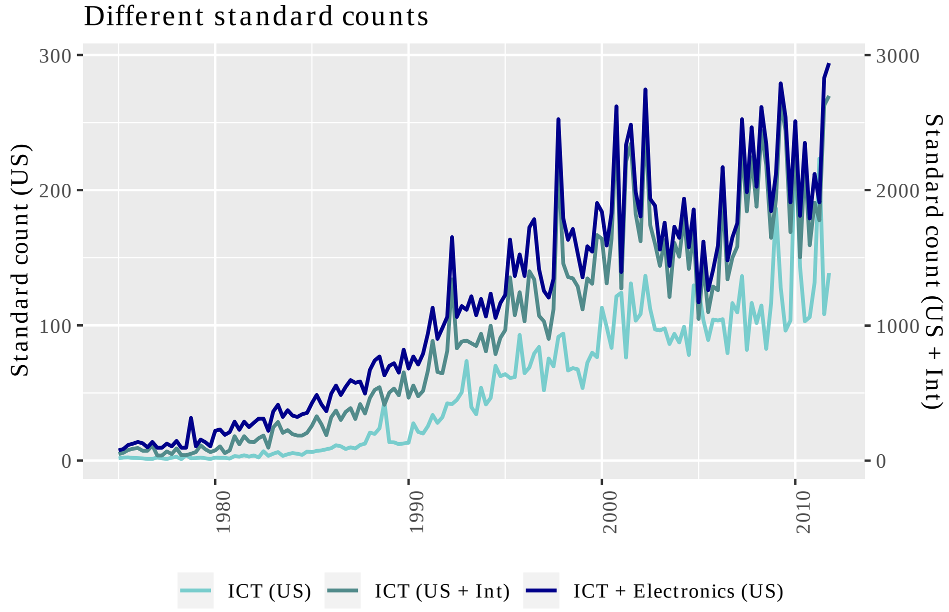
All results presented so far were obtained using a series of ICT standard documents released by US-based SSOs. In this section, we will analyze the robustness of our results by relaxing both the technological and the geographical definitions we used in computing the standard counts.

*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. the International Organization for Standardization, ISO). The most important and most relevant standards issued by these international bodies are generally accredited at US SSOs included in the baseline 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 important 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 appendix G).

*Second*, technological change 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 construct a series of US standard 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 baseline one (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 the standard count including both ICT and electronics (both from US SSOs) is stronger than the one between ICT standards from US SSOs only and the ones from all SSOs (international and US).

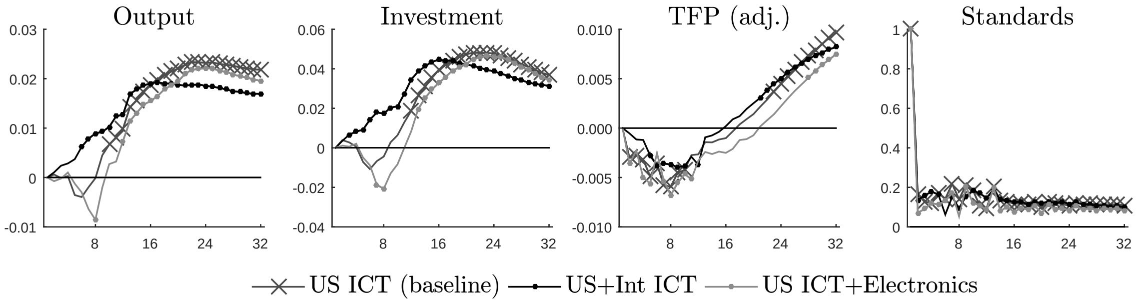
Figure 12: Standard series 1975Q1–2011Q4




*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 compare the results with the ones obtained in the baseline model. The IRFs from this robustness check are displayed in figure 13. Responses from the baseline model of figure 7 are displayed for comparison and the shock is normalized to one. The IRFs are qualitatively and quantitatively very similar to the results presented so far. We are therefore able to confirm our previous results with data series that include much larger numbers of documents. Results are not sensitive to the extension of the standard count to international SSOs or to a broader technological field.

Figure 13: IRFs – Larger definition of standard counts




*Notes*: Impulse responses to technology shocks identified from standardization data, using different definitions of relevant standards. "US ICT" corresponds to the standard counts in the baseline model. "US+Int ICT" denotes ICT standards (ICS classes 33-35) released both by US and international SSOs. "US ICT+Electronics" comprises ICT and electronics standards (ICS classes 31–37) which were released by US standard setting organizations. Lines represent the median responses to technology shocks identified from standardization data. Crosses and circles denote that the response is significant at the 16th/84th percentile. The unit of the x-axis is quarters.

## 6.2 Weighting standards by their relative importance

Our standard series attributes the same importance to every standard. As a first means to take into account the relative importance of individual standards, we weight standards by the number of references received from ulterior standard documents (forward-references). A standard references another standard if the implementation of the referencing standard necessitates the implementation of the referenced standard. The number of forward-references is thus a good indicator for the number of different applications in which a standard is used. 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 able to use standard documents released up to 2011 for this analysis).

A second way to control for the importance of standards is to weight standards by the number of pages. The number of pages is a plausible indicator for the technological complexity of the standard. SSOs and their members have an incentive to keep standards short in order to facilitate implementation. A standard document 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.

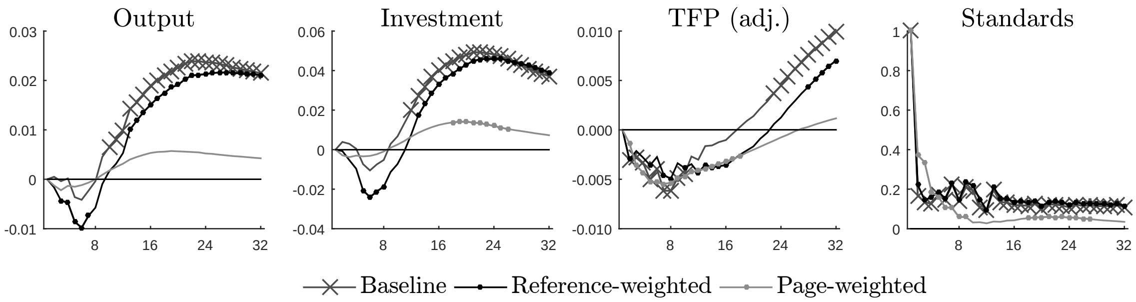
In particular, the two weighting schemes follow Trajtenberg (1990) who constructs citation-weighted patent counts. Similarly, we construct weighted standard counts

(WSC):

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

where $r$ denotes the number of references and $p$ denotes the number of pages (divided by 10) 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: IRFs – Different weighting schemes



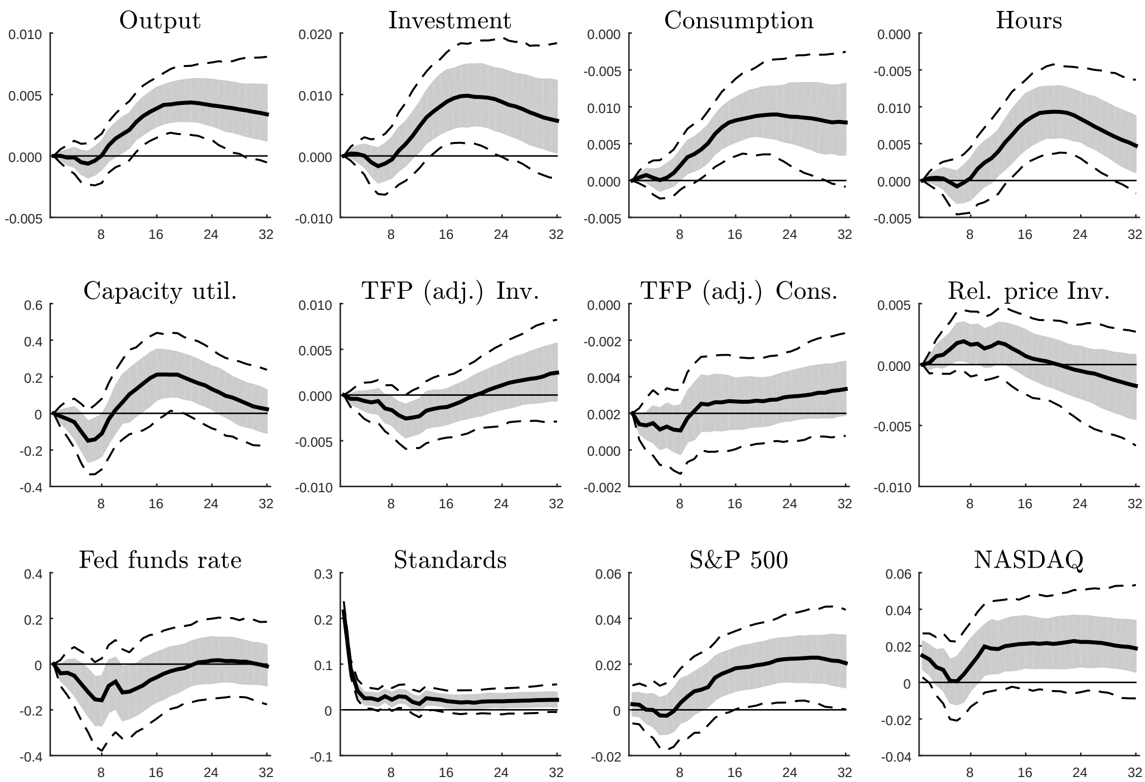

*Notes*: Impulse responses to technology shocks identified from standardization data, using different ways to weight the technological importance of a standard. "Reference-weighted" corresponds to the VAR model where the standard time series is weighted by the number of references of the underlying standard and "page-weighted" corresponds to the weighting scheme using the page number of each standard. Crosses and circles denote that the response is significant at the 16th/84th percentile. The unit of the x-axis is quarters.

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 7 are displayed for comparison). As before, we normalize the shock to one for better comparison. The results show that the dynamics hardly change. A shock to the reference-weighted series provokes a pronounced negative and significant response of TFP in the short-run, before picking up permanently. The response of TFP to innovations in the page-weighted count is significant at short horizons, but in general more muted. Variance decompositions mirror this finding. The contribution of the reference-weighted series is more important than the one using page-weights: 12% of the fluctuations of output at business cycle frequencies and 27% at longer frequencies are explained (compared to respectively 4% and 5%). In general, we find that weighting standard documents by references generates more pronounced dynamics than weighting by pages.

### 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 hyperparameter $\phi_1$. 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 as well as 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. All variables enter the VAR in log levels, except the Federal Funds rate and capacity utilization which are not logged.

Figure 15: IRFs – Large model




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

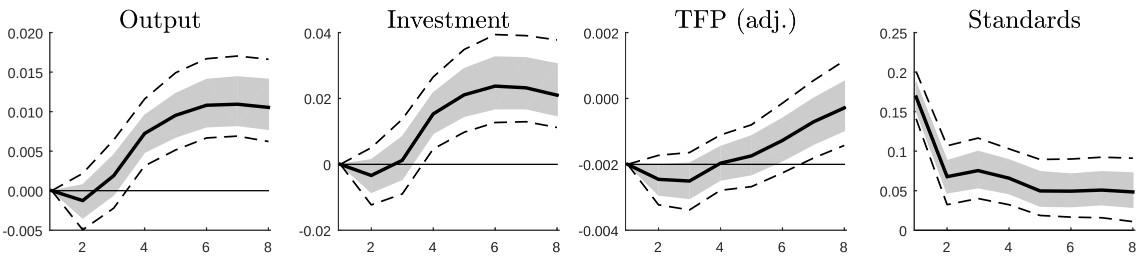
The results are displayed in figure 15. We first note that our results from the previous sections also hold in the larger system. The previously found results regarding the reaction of TFP seems to be driven by TFP in the investment sector. Figure 15 shows that the identified technology shock produces comovement of output, hours, consumption and investment. As before, there is slow diffusion.

The results in figure 15 also demonstrate that a reduction of the relative price of investment and a rise in capacity utilization only occurs in the medium-run. This is in line with our interpretation that standardization kicks off the implementation of the new technology, but it takes time until the new technology can be effectively used for the production of capital goods. Only when the technology has been implemented by a large number of producers can we expect to observe the reaction typically provoked by an IST shock. In particular, the relative price of investment decreases and one observes 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. In the case of our identified technology shock, we observe these reactions only in the medium-term, thus hinting to the existence of considerable implementation lags after a standardization event.

### 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.

Figure 16: IRFs – Annual data




*Notes*: Impulse responses to a technology shock identified from standardization data. The black line represents the median response, the corresponding shaded regions denote the 16th and 84th percentiles of the posterior distribution 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 very similar to the ones from quarterly data. The IRFs 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 2 years after which this expansion levels off. We also find the same short-term reaction for TFP as before: the IRF 2–3 years after the shock is negative before turning positive thereafter. In the long-run, TFP is increasing markedly.

## 7 Conclusion

This paper analyzes the role of standardization for macroeconomic fluctuations. Its main contribution is to exploit the microeconomic mechanisms of technology adoption for the macroeconomic analysis of technological change. The complex interdependencies of various technologies necessitate the coordinated establishment of common rules. This process of technological standardization is a crucial element of technology adoption. We therefore use data on standard releases in order to analyze the effect of new technologies on 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 a discrete decision, various technologies are interconnected, firms coordinate the development and adoption of interdependent technologies, technology diffuses slowly and its effects only materialize after considerable delay.

Although 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, the effects are more sizeable 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 transitory dynamics, we show that technology shocks can lead to an increase in productivity in the long-run, but the very nature of new technologies (and in particular discontinuous technological change) 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 increases constantly.

Our results also help to gain insight into the nature of shocks analyzed in the news shock literature. These news shocks are rarely linked to their specific underlying causes. This paper shows that standardization is a trigger of technology diffusion and therefore informs agents about future macroeconomic developments. For this reason, 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 proposes novel data and concepts originating from the literature on industrial organization and innovation economics to study the macroeconomic implications of technological change. Technology standards provide detailed information on the adoption of new technologies. This paper shows that this information can help opening the black box that technology and productivity often represent in macroeconomics. There are ample opportunities for future research on technological standardization. To this end, we make our data series available to researchers, to enhance our understanding of the role of technological innovation for both business cycles and growth.

# Technical appendix

## A Variance decompositions in the frequency domain

This appendix describes the computation of the variance decompositions in the frequency domain. We largely follow 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:

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

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:

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

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, $\Sigma$, can be decomposed in order to restrict the matrix C:

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

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

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

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:

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

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

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

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 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:

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

where $\iota_k$ 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 $\varepsilon_j$ to the variance of variable $Y_{t,k}$ at certain frequencies is consequently determined by:

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

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

This appendix describes the estimation procedure used throughout the paper. The reduced-form VAR system can be written 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 $a$, $\Omega$, $\Psi$ and $d$ are chosen to ensure a Minnesota prior structure. The literature has usually set the diagonal elements of $\Psi$, $\psi_i$, 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 $E(\Psi) = \text{diag}(\sigma_1^2, \dots \sigma_k^2)$ which approximates the Minnesota prior variance. Following Giannone *et al.* (2015), one can treat the diagonal elements of $\Psi$ 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 $\phi_{4,j}$. It can be shown that a Minnesota prior structure with variable-specific lag decay is imposed if the diagonal elements of $\Omega$ 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 $\phi_2$ being equal to one and $\phi_{4,j}$ 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 $\Sigma$ (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 $a$, $\Omega$, $\Psi$ 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 $\Theta$ which comprises $\phi_1$, $\phi_{4,j}$ and $\psi_i$ ($\phi_2$ and $\phi_3$ are fixed). Integrating out the uncertainty of the parameters of the model, the marginal likelihood conditions on the hyperparameters $\Theta$ that define the prior moments. Maximizing the marginal likelihood with respect to $\Theta$ is equivalent to an Empirical Bayes method (Canova, 2007; Giannone *et al.*, 2015) 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.*, 2015 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.* (2015) 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.

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.[37] More specifically, the prior is implemented by adding dummy observations to the system of VAR equations (Sims and Zha, 1998). The weight of each of the dummies corresponds to the respective prior variance.

## C Implementing block exogeneity

In section 5, we implement a block exogeneity VAR where we add series of investment components one by one to the baseline VAR. The purpose of this exercise is to ensure

[37] 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.

that the technology shock is identified as in the baseline model. This appendix describes the estimation procedure which follows Zha (1999).

We start from the structural representation of the VAR model:

$$F(L)Y_t = \varepsilon_t \quad \text{where} \quad F(L) = B_0 - B(L)$$

The structural model can be split in several blocks. Since we are working with two blocks in section 5, the following illustration concentrates on this case; but the exposition also holds for the general case of several blocks (see Zha, 1999).

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

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 (for $i = 1, 2$):

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

Replace $F(L) = B_0 - B(L)$ in the normalized VAR system:

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

Each block 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 on 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 $\Sigma_{ii}$. We therefore employ a Gibbs sampler to alternately draw $\Sigma_{ii}$ 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, i.e. $\phi_1$, $\phi_{4,j}^{(1)}$ 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 $\phi_1$, $\phi_{4,j}^{(1)}$ 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

The implications of slow technology diffusion pose macroeconometric challenges which require the use of meaningful information about technology adoption (Lippi and Reichlin, 1993; Leeper *et al.*, 2013). This problem is known as non-fundamentalness and described in this appendix. 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, 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 $\varepsilon_t$, 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.

Non-fundamentalness can arise in models of slow technology diffusion or news shocks. For example, 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.*, 2013) 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.

In a nutshell, there are two ways to solve the non-fundamentalness problem. The first one consists in modelling information flows directly which involves making very strong assumptions about time lags and functional forms of diffusion processes (i.e. $\overline{K}(L)$) or the way news shocks materialize. The second one is about using direct measures of news or diffusion which is the approach taken in this paper.

## Data appendix

This data appendix describes the construction of the investment rates and ICT dependency ratios in section 2 (data appendix E). The table in data appendix F lists all the data sources for the empirical analyses in sections 4–6. Information on the construction of the standards data can be found in data appendix G.

### E Data on investment rates and ICT dependence

We compute investment rates and a measure of ICT dependence for 61 industries (listed below).

The investment rate is defined as current investment in industry $j$ scaled by last period's capital stock. Data are taken from the BEA's Fixed Assets accounts (section 3); the investment rate is the ratio of investment in private fixed assets (table 3.7) over the current-cost net stock of private fixed assets (table 3.1) which is lagged by one year. We consider investment in private fixed assets ("Total") as well as the disaggregation into investment in private equipment ("Equipment"), investment in private intellectual property products ("IP") and investment in private structures ("Structures").

For our measure of ICT dependence we rely on the BEA's input-output tables (use tables before redefinitions). Dependence on ICT inputs is defined as the share of a sector's inputs from the following sectors in overall inputs: (1) Computer and electronic products [NAICS 334], (2) Publishing industries, except internet (includes software) [NAICS 511], (3) Broadcasting and telecommunications [NAICS 513], (4) Data processing, internet publishing, and other information services [NAICS 514] and (5) Computer systems design and related services [NAICS 5415].

There are reporting breaks in the BEA input-output data which necessitate that we aggregate certain sectors up in order to have consistent time series. As the fixed assets tables do not contain information on the government sector, we drop these from the dataset.

Table E1: Industries

| BEA code | Industry description | BEA code | Industry description |
|---|---|---|---|
| 111CA | Farms | 484 | Truck transportation |
| 113FF | Forestry, fishing, and related activities | 485 | Transit and ground passenger transportation |
| 211 | Oil and gas extraction | 486 | Pipeline transportation |
| 212 | Mining, except oil and gas | 487OS | Other transportation and support activities |
| 213 | Support activities for mining | 493 | Warehousing and storage |
| 22 | Utilities | 511 | Publishing industries, except internet (includes software) |
| 23 | Construction | 512 | Motion picture and sound recording industries |
| 321 | Wood products | 513 | Broadcasting and telecommunications |
| 327 | Nonmetallic mineral products | 514 | Data processing, internet publishing, and other information services |
| 331 | Primary metals | 521CI | Federal Reserve banks, credit intermediation, and related activities |
| 332 | Fabricated metal products | 523 | Securities, commodity contracts, and investments |
| 333 | Machinery | 524 | Insurance carriers and related activities |
| 334 | Computer and electronic products | 525 | Funds, trusts, and other financial vehicles |
| 335 | Electrical equipment, appliances, and components | 531 | Real estate |
| 3361MV | Motor vehicles, bodies and trailers, and parts | 532RL | Rental and leasing services and lessors of intangible assets |
| 3364OT | Other transportation equipment | 5411 | Legal services |
| 337 | Furniture and related products | 5415 | Computer systems design and related services |
| 339 | Miscellaneous manufacturing | 5412OP | Miscellaneous professional, scientific, and technical services |
| 311FT | Food and beverage and tobacco products | 55 | Management of companies and enterprises |
| 313TT | Textile mills and textile product mills | 561 | Administrative and support services |
| 315AL | Apparel and leather and allied products | 562 | Waste management and remediation services |
| 322 | Paper products | 61 | Educational services |
| 323 | Printing and related support activities | 621 | Ambulatory health care services |
| 324 | Petroleum and coal products | 622HO | Hospitals and nursing and residential care facilities |
| 325 | Chemical products | 624 | Social assistance |
| 326 | Plastics and rubber products | 711AS | Performing arts, spectator sports, museums, and related activities |
| 42 | Wholesale trade | 713 | Amusements, gambling, and recreation industries |
| 44RT | Retail trade | 721 | Accommodation |
| 481 | Air transportation | 722 | Food services and drinking places |
| 482 | Rail transportation | 81 | Other services, except government |
| 483 | Water transportation | | |

## F Macroeconomic data sources

| Variable | Description | Source | Details |
|---|---|---|---|
| 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 |
| Types of investment | Equipment | Bureau of Economic Analysis (BEA) NIPA table 5.3.3 lines 9–19 | Index (2009=100), seasonal and per capita adjustment |
| | Information processing equipment | | |
| | Computers and peripheral equipment | | |
| | Other equipment | | |
| | Industrial equipment | | |
| | Transportation equipment | | |
| | Other equipment | | |
| | Intellectual property products | | |
| | Software | | |
| | Research and development | | |
| | Entertainment, literary, and artistic originals | | |
| 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 |
| Share prices | Individual firms' share prices | Bloomberg | End-of-day prices |

## G Construction of standards data

**Data source.** We obtain information on standard releases from the Searle Center database on technology standards and SSOs (Baron and Spulber, 2018). The Searle Center database draws information from various sources, including PERINORM, IHS Standards Store, DocumentCenter and the websites of various SSOs. PERINORM is a database with bibliometric information on standards, which is hosted by the national SSOs of France, Germany and the UK, but also includes information on standards issued by a large number of other organizations. In particular, PERINORM provides data on standards issued by 20 of the most relevant SSOs in the US. PERINORM comprises detailed bibliographic information on more than 1,5 million standard documents. IHS Standards Store and DocumentCenter are online stores offering standard documents for sale. The websites provide free access to bibliometric information on standards, such as title, technological class, publication date, references and the identity of the issuing SSO. IHS Standards Store and Document Center provide this information for the standards issued by more than 600 SSOs. In addition to these sources, the Searle Center database uses data directly obtained from several of the most relevant SSOs, including 3GPP (3rd Generation Partnership Project) and IETF (Internet Engineering Task Force).

The initial dataset comprises standard documents issued by a US (469,859 documents) or international SSO (308,798 documents). 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.

**Data transformations.** In a first step, we restrict the sample to standard documents issued by an organization with the country code "US". This results in a list of 474 SSOs. Our sample includes the most established formal SSOs, such as the American Society for Testing and Materials (60,653 standard documents), the American National Standards Institute (37,390 standards documents), and the Society of Automotive Engineers (23,803 standards documents).[38] In addition, our dataset includes a large number of smaller SSOs and consortia. Our sample consists in both standards that are originally produced by one of these 474 organizations and in stan-

[38]While the American National Standards Institute (ANSI) does not develop standards itself, standards developed by SSOs accredited by ANSI are often co-published by the developing SSO and ANSI.

dards 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/release of a standard in the sample).

Many important international standards enter the sample when they receive accreditation by an American SSO. It is e.g. very common that international standards developed at the International Organization for Standardization (ISO) or the International Telecommunication Union (ITU) are published as *American Standards* by a US SSO. Other international standards can however also be directly relevant to the US economy. We therefore carry out a robustness analysis in section 6.1 covering also standard documents issued by international organizations (such as ISO). Once again, we remove duplicates using information on standard equivalence. If a standard was first developed by an international SSO and eventually accredited by a US SSO, the standard is included only once, but the standard release date for this analysis is defined as the date of publication at the international SSO, whereas it is the date of publication at the US SSO in the analysis using only US standards.

Including standards from international standards bodies allows for instance covering many of the most relevant 3G and 4G mobile telecommunication standards applying in the US. Many of these standards were set in a worldwide effort in the Third Generation Partnership Project (3GPP). The World Administrative Telegraph and Telephone Conference (WATTC) in 1988 aimed at the international harmonization of telecommunication standards and led to the inclusion of a large number of already existing national standards in the ITU standard catalogue. These standards do not represent the adoption of new technology. We therefore exclude standards that were released by ITU in the forth quarter of 1988 and that were released in the ICS classes 33.020 ("Telecommunications in general") and 33.040 ("Telecommunication systems").

In a second step, we restrict the sample by technological field. We rely upon the International Classification of Standards (ICS)[39]. 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.[40] We also perform analyses

[39]For more details, see the below table G1 and http://www.iso.org/iso/ics6-en.pdf.

[40]For instance, standards in these classes account for 98% of all declared standard-essential patents (Baron and Pohlmann, 2018).

on a wider definition of ICT, including ICS classes 31 ("Electronics") and 37 ("Image Technology").

We count the number of standard documents released per quarter. In several cases, the Searle Center database only includes information on the year, but not the month of standard release. For the series containing standards from US SSOs only ("US"), we have information on both the quarter and the year of release for 71% of the standards in the period 1975Q1–2011Q4. For the series which contains both standards from US and international SSOs ("US+Int"), this information is available for 82% 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.

**Accounting for the importance of different standards.** In section 5.2, we distinguish between new and upgraded standards. A standard upgrade is a new version replacing an older version of the same standard. We thus identify all standard documents which replace a preceding version of the same standard and those which constitute genuinely new standards.

Standards differ significantly in their economic and technological importance. In order to account for this heterogeneity, we implement different weighting methods in section 6.2. *First*, we weight the number of documents by the number of times a standard is referenced by ulterior standard documents. In order to compare 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 able to use standard documents released up to 2011 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 standard references are made within the first four years after release. *Second*, we weight standard documents by the number of pages. For each standard document, we observe the number of pages from the Searle Center database. In the case where such information is not available for a standard, we use the average number of pages by quarter and ICS class computed from all those standards where such information is available.

**Publicly available version.** We provide the baseline series for the US (along with the counts for new versions only as well as the reference-weighted and page-weighted counts) on the authors' websites in order to encourage researchers to use these series. For transparency, we also provide the code used to transform the data. Users wanting to modify any of the parameters of the time series (such as technology class, international or national scope, weighting) to generate alternative time series using the same raw data need access to the Searle Center Database[41]. They can follow the database access instructions and download the respective folders which contain the data to be used.

[41] http://www.law.northwestern.edu/research-faculty/clbe/innovationeconomics/data/technologystandards/index.html

Table G1: 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)

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