Patent-Based News Shocks*

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Abstract

In this paper we exploit firm-level data on patent grants and subsequent reactions of their stocks to identify technological news shocks. Changes in stock market valuations due to announcements of individual patent grants represent expected future increases in the technology level, which we refer to as *patent-based news shocks.* Our patent-based news shocks resemble diffusion news in that they do not affect total factor productivity in the short-run but account for about 20 percent of its variations after five years. These shocks induce positive comovement between consumption, output, investment and hours. Unlike the existing empirical evidence, patent-based news shocks generate a positive response in inflation and the federal funds rate, in line with a standard New Keynesian model. Patenting activity in electronic and electrical equipment industries within the manufacturing sector and computer programming and data processing services within the services sector play a crucial role in driving our results.

Keywords: News Shocks, Patents, Patent-based news shocks
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1 Introduction

Ever since the seminal work of Beaudry and Portier (2006) revived the idea of expectation-driven business cycles in Pigou (1927), many economists have tried to understand the role that so-called technological news shocks play in explaining business-cycle fluctuations.[1] Technological news shocks are usually defined as advance information about technological improvements that will become available in the future. Isolating these technological news shocks requires two elements: first, a reliable measure of technological improvements and, second, an identification strategy to extract the advance information about these improvements.

The empirical news literature almost exclusively uses the utilization-adjusted total factor productivity (TFP) in Fernald (2012) as a measure of technological improvements, and defines technological news shock as the shock that does not affect TFP in the short run but drives most of its variations over longer horizons.[2,3] Neither of these two elements is free of concerns. First, TFP is an *indirect* measure of technology that is hard to link to specific technological improvements. Second, regardless of the specific assumptions imposed, existing identification schemes rely on strong assumptions that the TFP follows an exogenous process and that, consequently, long-run movements in TFP are solely due to productivity shocks.[4]

This paper contributes to the empirical literature by using a *direct* measure of technological improvements and by proposing a straightforward identification strategy that is agnostic about the TFP process. We use microlevel data on patents that are, as noted by Griliches (1990), by definition directly related to inventiveness. In particular, we use the measure of technological innovation in Kogan, Papanikolaou, Seru, and Stoffman (2017) (KPSS, henceforth), and refer to it as patent-based innovation index because it combines firm-level data on patent grants with their subsequent stock price movements.[5] These stock price movements represent the reaction

[1]See, for example, Beaudry and Portier (2006), Jaimovich and Rebelo (2009), Barsky and Sims (2011), Kurmann and Mertens (2014), Beaudry and Portier (2014), Schmitt-Grohé and Uribe (2012), Forni et al. (2014), and Görtz and Tsoukalas (2017).

[2]The TFP in Fernald (2012) is constructed following his earlier work in Basu et al. (2006). Even though this measure arguably represents the best aggregate measure of technology at a quarterly frequency, it does not fully coincide with the annual purified technology measure proposed by Basu et al. (2006) as it does not correct for the possibility of non-constant returns to scale. As pointed out by Bouakez and Kemoe (2017) even this seemingly small discrepancy between the two measures can have important implications on the conclusions regarding the effects of news shocks. In addition, Cascaldi-Garcia (2017) and Kurmann and Sims (2017) show that the existing identification schemes are very sensitive to updates recently implemented by Fernald to his original TFP measure.

[3]Barsky and Sims (2011) identify technological news shock as a shock that explains most of the forecast error variance of TFP over a 40-quarter horizon, restricting it to have zero impact effect on TFP. Some researchers in this literature have adopted the approach of Francis, Owyang, Roush, and DiCecio (2014) and identified technological news shocks as shocks that explain most of the forecast error variance of TFP at the 40-quarter horizon, restricting it to have zero effect on TFP on impact. More recently, Kurmann and Sims (2017) propose using the approach of Francis et al. (2014) but without imposing a zero-impact restriction.

[4]For example, as pointed out by Barsky and Sims (2011), other structural shocks that can affect productivity in the future but not immediately, such as research and development shocks, investment-specific shocks or reallocative shocks would be confounded with true news shocks when maximum variance decomposition of TFP is used, thus misrepresenting the importance of technological news shocks in driving the business cycle.

[5]The authors calculate an economic value of each patent based on the firm's stock price reaction to news about a patent grant, while controlling for the factors that could move stock prices but are unrelated to the

of markets to announcements about technologies that will become available in the future, which maps directly into the definition of technological news shocks.

The advantage of using this direct measure of future technology is that, unlike most of the empirical news literature, we can use a very simple and straightforward identification strategy. In particular, we identify the *patent-based news shock* as the shock that explains most of the contemporaneous variations in the measure that aggregates stock market valuations of all individual patents. We show that this shock essentially amounts to an unexpected contemporaneous shock. An increase in the patent-based innovation index represents the market valuation of the potential patent outcomes, capturing expectations about technology that will be available with some delay.

The news shocks identified with our approach are more closely connected to true technological improvements for at least two reasons. First, our approach uses data on technology together with forward-looking variables that reflect advance information about future improvements in order to recover the structural shock. As we already discussed, using movements in TFP for identification might be problematic, so it does not come as a surprise that even small updates in TFP lead to different conclusions regarding the effects of technological news shocks. At the same time, aggregate stock prices, often used in this literature, are also likely to capture changes not related to economic fundamentals, such as optimism or animal spirits. By using microlevel data, our approach mitigates these issues, as the KPSS measure considers only movements in market responses during a narrow window of time around patent grant announcements. Therefore, any surprise movements in the KPSS should measure market expectations solely about future technological improvements reflected in patents.[6]

Second, long lags between a patent grant and the appearance of the patented product or process account for a delay in the implementation of technology. This delay makes patents more appealing for identifying news shocks than alternative direct measures that capture technological improvements around their implementation dates (see, for example, Alexopoulos, 2011; Alexopoulos and Cohen, 2009). Overall, patents represent a good proxy for a technology that will be available and diffuse with a delay, while movements of the firm's stock price within a very short window around the patent grant date represent the market expectations about this technology. Indeed, the key idea behind expectation-driven business cycles is that markets

economic value of the patent.

[6]It is important to note that the use of simple patent counts is often criticized in the literature because it does not account for drastic differences in technical and economic significances across patents. It follows that a simple patent count may either underestimate or overestimate the real (expected) economic effect of such innovations. In addition, patents are used differently across fields and do not always reflect how the firm appropriates returns from innovation (Sampat, 2018). The KPSS measure overcomes these issues by carefully weighting patents by their economic importance reflected in the stock market movements following the announcements of patent grants. Furthermore, the patent-based innovation index is given in terms of dollars and, therefore, can be comparable across time and industries. Although this measure does not overcome the criticism that patent fluctuations might be the consequence of changes in patent laws and/or the quantity of resources available to the U.S. patent office, it does mitigate it by assigning these patents more appropriate weights. Furthermore, our results are robust to using average patent value, a measure that completely overcomes this criticism, suggesting that it is not changes in patent laws that drive our results.

learn about a new technology before it is implemented, which is precisely what the patent-based innovation index captures.

Our results show that the response of TFP to the patent-based news shocks closely resembles the predicted path of *diffusion news* described by Portier (2014), as they seem to "bring information about the future evolution of TFP without affecting TFP in the short run." In fact, our news shocks do not significantly move TFP for about six quarters in our benchmark specification. Strikingly, this is a result of the identification and not an imposed assumption; Beaudry and Portier (2006) only achieve such diffusion by imposing it through statistical procedures, and Barsky and Sims (2011) show TFP quickly growing to a new higher level, which is less compatible with the idea of diffusion news. Because of this feature, our results are also much less susceptible to the criticism that expansions following news shocks are not due to the effects of news *per se*, but rather to the expected change in fundamentals evoked by news innovations.

The identified patent-based news shocks induce a clear comovement among output, consumption, investment, and hours. They all rise on impact, displaying hump-shaped responses; the majority of these movements happen even before the positive effect on TFP becomes significant and TFP starts picking up. This result indicates that the identified shock carries advance information about future productivity prospects, rather than tracking its path. This anticipation feature of the patent-based news shock is further confirmed by the strong positive impact effect on the two forward-looking variables, stock prices and consumer confidence.

Another important result of our analysis relates to the responses of inflation and the federal funds rate to the patent-based news shock. Both variables respond positively in the short run, consistent with the predictions of a standard New Keynesian model. This result becomes even more relevant in light of the fact that most of the empirical literature suffers from a so-called disinflation puzzle – a persistently negative response of inflation to a positive news shock. Bouakez and Kemoe (2017) show that the existence of this puzzle in the empirical news literature is the direct consequence of measurement errors in TFP that impair the identification of technological news shocks.[7] Because our identification does not rely on any assumptions regarding TFP, this result reinforces the claim that the patent-based news shocks we identify represent "true" technological news shocks.[8]

The news shocks identified here explain less of the forecast error variance of main macroeconomic aggregates than typically found in the empirical literature on news shocks. This result is expected, because most identification schemes are based precisely on maximizing the forecast

[7] In addition, these authors also confirm that technological news shocks in the Smets and Wouters (2007) model are indeed mildly inflationary.

[8] As pointed out by Barsky and Sims (2009), in order to make TFP-based empirical news literature findings consistent with a New Keynesian model, one would need to account for additional features, such as exogenous real wage rigidity or monetary policy that reacts to output growth rather than output gap. Furthermore, Jinnai (2013) shows that these modifications are not enough in a model with endogenous capital, and proposes two additional ones: sticky nominal wages in the labor market and a monetary policy rule that reacts to consumption growth rate. Our results show that all these additional modifications are not needed in the first place.

error variance of TFP over a particular horizon. We believe that our results represent a lower bound of the importance of technological news shocks given that not all innovative activity is patented in the first place, and the patent-based innovation index only considers publicly listed companies. Nevertheless, the patent-based news shocks explain almost zero short-run variations in TFP and about 20 percent of variations at a five-year horizon.

We also provide industry evidence, where we show that patenting activity in manufacturing and services is predominantly responsible for explaining future movements in TFP. Within manufacturing, the most important industries are Electronic and electrical equipment, Machinery and Chemicals. Interestingly, a patent-based news shock identified only considering these industries produces a perfect zero effect on impact, before slowly growing to a new higher level. Another important industry, Business services, produces a significant positive effect on impact, also increasing in the long-run. This positive impact effect is expected, as this industry is driven by services related to computer programming and data processing which can be available more promptly to the market than manufacturing goods.

We show that our main results are robust to using the patent-based innovation index as an instrument for innovative activity in a proxy VAR setting by following the methodology developed in Stock and Watson (2012) and Mertens and Ravn (2013). As the patent-based innovation index aims to capture exogenous stock price movements due to expected future economic fundamentals, it represents a good candidate for a proxy for technological news shocks. The idea of using proxy VARs to identify technological news shocks is recent and, to the best of our knowledge, initiated by Cascaldi-Garcia (2018), who employs forecast revisions from professional forecasters as exogenous instruments. Miranda-Agrippino et al. (2019) also propose a proxy for technological news shocks, based on the number of patents registered with the USPTO. However, as previously discussed, the sole use of patent counts can underestimate or overestimate the real (expected) economic effects of patented innovations.

This paper is also linked to the literature that relates patents to technological development. The idea of using patent data to identify surprise technology shocks has been explored by Shea (1999) and Christiansen (2008). The former uses data on patent applications and research and development expenditures in 19 U.S. manufacturing industries to recover technology shocks, concluding that favorable technology shocks do not significantly increase measured TFP at any horizon. Christiansen (2008) uses more than a century of annual data on patent applications and investigates effects of patent shocks on inputs and labor productivity.

Our paper is organized as follows. Section 2 argues why patents and their stock market valuations can be used to identify technological news shocks. Section 3 describes the data and the identification procedure. Section 4 presents the main results. Section 5 discusses the relation of our patent-based news shocks to traditional TFP-based news shocks and to unexpected innovations in other forward-looking variables. Section 6 presents the robustness of our results when proxy VAR with the patent-based innovation index as an instrument is used. Section 7 concludes.

2 Patent-Based News Shocks

The news literature usually defines technological news shocks as advance information about technology that will become available with some delay. Rarely, however, does this literature provide specific examples of such technological advances. Instead, it almost exclusively relies on using TFP as an abstract aggregate measure of technology and explores its movements over the business cycle to identify aggregate technological news shocks.

We identify technological news shocks using a measure, proposed by KPSS, that combines microlevel data on patents together with their stock market valuations. This approach overcomes the restriction that TFP is an abstract and imperfect measure of technology by relying on the importance of microlevel data to learn about relevant aggregate shocks.[9] We argue that unexpected innovations in this measure represent technological news shocks and refer to them as *patent-based news shocks*.

Patents contain useful information about inventive activity of an economy.[10] Furthermore, as argued by Griliches (1990), analyzing data on patents together with the data on stock market valuation is particularly useful because of the immediate nature of stock market reactions to the events that are a result of firms' research activities. At the same time, the author notes that a downside of using stock market data is its large volatility, arguing that "the needle might be there but the haystack can be very large." We argue that specific stock market variations exploited by KPSS bring us much closer to finding this needle and, consequently, to identifying technological news shocks.[11]

2.1 KPSS Innovation Index

The KPSS aggregate innovation index is constructed by using rich firm-level datasets. In particular, the authors estimate the economic value of the patent by combining data on patents issued to U.S. firms during the 1926-2010 period with firm stock price movements.[12] The biggest challenge these authors face is to carefully extract the information about the economic value of

[9]When learning about an aggregate shock that might represent a relevant force behind business cycles, it is always useful to consult more data. For example, Romer and Romer (2004) use a narrative approach by reading accounts of each Federal Open Market Committee meetings to identify monetary policy shocks and, similarly, by analyzing presidential speeches and congressional reports to identify tax shocks in Romer and Romer (2010). Nakamura and Steinsson (2014) exploit variation in regional military procurements to estimate the effects of government spending. Using microdata becomes particularly relevant in the case of technological news shocks, given the imperfections related with TFP as an aggregate measure of technology.

[10]As Griliches (1990) writes "the stated purpose of the patent system is to encourage invention and technical progress both by providing a temporary monopoly for the inventor and by forcing the early disclosure of the information necessary for the production of this item or the operation of the new process."

[11]Several authors have explored stock valuations of patentable assets. See, for example, Austin (1993), Nicholas (2008), and Hall et al. (2005). However, none of these studies is as broad, both in firm and time dimension, as the KPSS one.

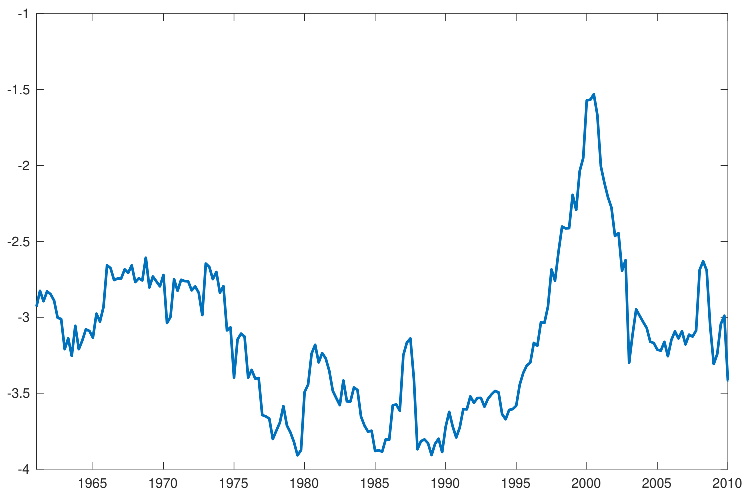
[12]In particular, the authors use about 7.8 million patents available from Google Patents and then match all patents to corporations whose returns are in the Centre for Research in Security Prices (CRSP) database. After matching the names of assignees to public firms in CRSP, they obtain a database of 1,928,123 matched patents. We refer the reader to the original article for more details regarding the dataset construction.

the patent contained in stock prices from unrelated news. To do so, they focus their analysis on the days around an announcement of a patent grant, which are also characterized by larger trading activity in the stock of the firm. They then filter the stock price reaction to the patent issuance from noise by making several distributional assumptions; the results prove to be quite robust to these assumptions.

The value of each patent in the database is calculated as a part of the stock reaction that is solely due to news about a patent grant. One can then aggregate firm-level information to obtain an aggregate innovation index. In order to do so, particular assumptions must be made about how monopoly profits of the firms, accumulated because of the patent issuance, relate to aggregate improvements in technology. The authors propose a simple model of innovation as in Atkeson and Burstein (2011), in which firms collect monopoly profits from innovation; these profits, in turn, are approximately linearly related to aggregate improvements in output and TFP. Therefore, an aggregate measure (equation 18 in the original article) is the sum of the value of all patents granted in year t to the firms in their sample, scaled by aggregate output.

The aggregate index constructed following the above procedure is in an annual frequency. Crucially for our analysis, we were able to construct an analogous measure in a quarterly frequency, as displayed in Figure 1.[13] We refer to this measure as the *patent-based innovation index*.

Figure 1 Quarterly Patent-Based Aggregate Innovation Index



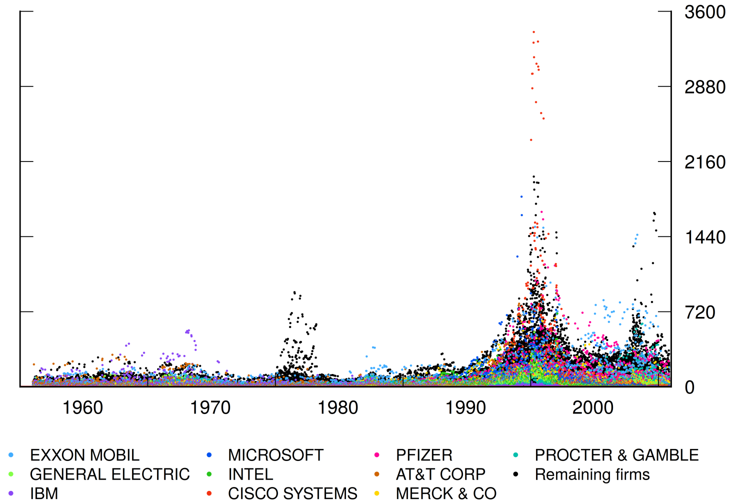
Note: Log of the aggregate patent-based quarterly index constructed following the procedure described in Kogan et al. (2017), spanning 1961:Q1 - 2010:Q4.

The value of the index seems to follow times of speculation in the market and especially

[13] The authors make available information on patent grant dates, the inferred economic value of each patent and the number of citing patents, which allows us to construct the quarterly aggregate index. Although KPSS provide an annual measure for the 1926-2010 period, we are only interested in studying the period after 1961:Q1, because of the availability of macroeconomic data that we use in our benchmark analysis. In particular, the data on consumer confidence are available only after this date, which is, therefore, the earliest starting date in any specification.

that of the dot-com bubble, where investors appear to have been actively following technological patents. Throughout the entire sample, the distribution of patents assigned to the firms is highly skewed. There are few high-frequency patenting companies in the sample. For example, during the sample Exxon Mobil was granted, on average, 240 patents per year, Cisco about 332, and IBM 1,384. To put these numbers into perspective, the median number of patents per company per year is 3, and the average number is about 29. Figure 2 represents the top 10 firms by their patent value from 1961 to 2010 with all their patent values throughout the sample.[14]

Figure 2 VALUE OF PATENTS BY COMPANY



Note: The figure shows values (in 1982 dollars) of each patent by top 10 firms.

Figures 3 and 4 represent the share of total number (and value) of patents by top 10 firms in each year. The share of these firms, both in terms of number and value of patents, is consistently higher than 25 percent and, in some periods, even as high as 50 percent.

2.2 Bridging the Theoretical and Empirical Technological News

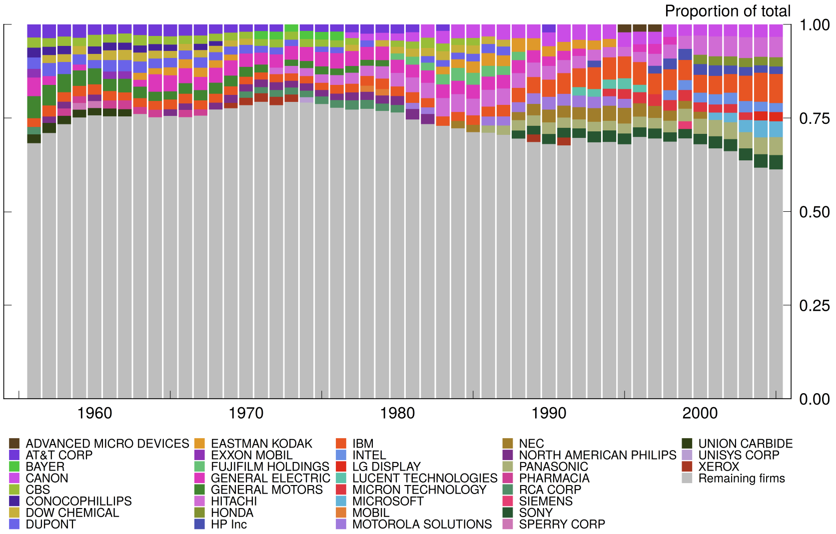
A few reasons lead us to believe that the patent-based innovation index can be used to extract technological news shocks.

First, by combining patent counts with stock market data, this measure overcomes the criticisms that arise when only simple patent counts are used for economic analysis, which pertain to the issue of drastic differences in technical and economic significances across patents. Specifically, this measure carefully extracts the economic value of each patent by capturing firm stock market movements in response to news about patent grants; these stock market valuations, in turn, are used as weights for the economic importance of each patent.[15]

[14] Nicholas (2008) investigates valuations of corporate patentable assets in an earlier period, from 1910 to 1939, and also finds that the distribution of patents is highly skewed, with few companies dominating patenting activity.

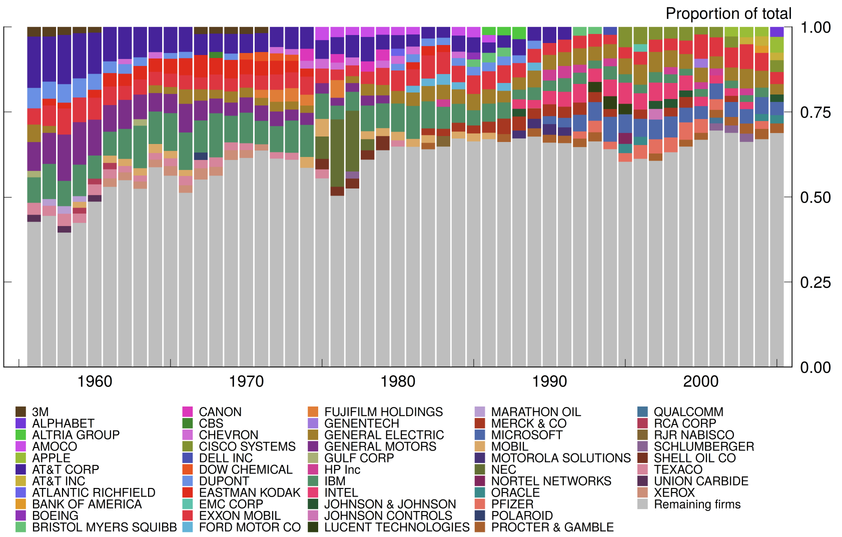
[15] Another "quality-adjusted" measure of patents often used in the literature is citation counts, as discussed by Hall, Jaffe, and Trajtenberg (2005). It turns out that this measure is highly correlated with the KPSS measure.

Figure 3 Top Firms by Number of Patents per Year



Note: The figure shows the share of number of patents by top 10 firms in each year from 1961 to 2010.

Figure 4 Top Firms by Total Patent Value per Year



Note: The figure shows the share of total value of patents by top 10 firms in each year from 1961 to 2010.

Second, while lags between a patent grant and the date when a product or process that is patented is brought to markets might be worrisome when one is interested in recovering surprise technological shocks (see, for example, Alexopoulos, 2011), they represent a desirable feature when one is interested in recovering technological news shocks. Indeed, the key idea behind expectation-driven business cycles is that markets learn about a new technology before it is implemented, which is precisely what the patent-based innovation index captures.

Third, any plausible identification of technological news shocks must rely on the usage of forward-looking variables because of their predictive power regarding future movements in economic activity, as recognized by Beaudry and Portier (2006). For that purpose, the literature has often used movements in aggregate stock prices and consumer confidence to extract the forecastable component of TFP. However, these movements also capture changes not related to economic fundamentals, such as optimism, confidence, and animal spirits. By narrowing the forward-looking component to the specific market responses to announcements of patent grants, the patent-based measure is more prone to capture market expectations only based on future economic fundamentals.

Fourth, identifying technological news shocks by looking at unexpected movements in a measure that collects market expectations about the future value of a technological innovation circumvents the issues that arise when the identification relies on TFP measures. Fernald (2012) calculates a utilization-adjusted TFP series that is widely used by the news shock literature as a proxy for the technological level of the U.S. economy. The process of extracting the technological level is complex and depends on imputations on hours worked and capital level as well as on filters to estimate the utilization factor. As a result, the series is subject to measurement errors and data revisions.

As pointed out by Cascaldi-Garcia (2017) and Kurmann and Sims (2017), the identification of news shocks is not robust to different vintages of this series. The Barsky and Sims (2011)' identification, for example, relies on the assumption that this series perfectly captures the technological level of the economy, and that it is driven by only two shocks: surprise and news shocks. It follows that movements in forward-looking variables that can explain future movements in TFP should represent a news shock. This claim, however, does not hold if TFP is measured with an error. Our identification instead depends only on the patent-based innovation index series, and it is agnostic about the measurement of TFP.

Overall, rather than focusing on proposing a novel statistical approach that would recover news shocks by exploiting fluctuations in TFP, we approach this problem differently, by using microlevel data on patents and their stock market valuations. Because this measure represents a forward-looking measure that collects market expectation about the future value of an innovation, any unexpected changes in this measure would represent news about the future value of these innovations.

2.3 Some Illustrative Examples

Although a firm that applies to patent a technology might start using the technology during or even before the application process, it is only after the technology is patented that the information about it becomes public knowledge. This information can then be used by competitors for advancing their own technological ideas. Therefore, it is likely that the effects of a technological discovery that is admissible for being patented will be reflected in the aggregate TFP only after the patent is granted.

We provide several examples in order to establish the relationship between a patent grant, the reaction of the firm's stock price to that grant, and the subsequent implementation of technology and its effect on competitors.

First we consider patent 5,064,435, titled "Self-expanding prosthesis having stable axial length," which was granted to Schneider (USA) Inc. on November 1, 1991. This patent represented an improvement over plastically expanded stents used until that time. The patent was assigned a very high economic value, placing it in the top 15 percent in 1991. With 788 forward citations, the patent was the 25^{th} most-cited patent in the entire sample and the second most-cited patent in 1991, indicating its high scientific value as well. Interestingly, even though the U.S. Food and Drug Administration approved the stent use only two years after the patent grant, it was already cited about 40 times within the first two years of its grant, suggesting that the information released in the patent was widely used for the development of other technologies.

Another example that illustrates the importance of the dissemination of the information released with a patent grant is patent 4,131,919, awarded to Eastman Kodak Company on December 26, 1978, for the invention of the "electronic still camera that employs a nonvolatile reusable storage medium for recording scene images"– the first self-contained digital camera. Although Kodak didn't make a camera that used digital single-lens reflex commercially available until 1991, the information contained in this patent was crucial for the development of competing technologies and for the overall advancement of the field of photography and imaging. The information was invaluable for competitors that understood the importance of digital technology even more than Kodak itself and produced a commercially available digital camera in 1986.[16] The patent value was the third highest in 1977. Its scientific value was very high as well; the patent was cited 100 times, placing it in the top 1 percent of cited patents in the entire period.

Patent 4,699,545, granted to Exxon Production Research Company on October 13, 1987 and titled "Spray Ice Structure," is an example that confirms the narrative behind technological news shocks. The patent is for a method of creating a structure to protect against ice sheets when drilling offshore arctic wells, and it presents a "fast, economical and practical approach for drilling offshore arctic wells in areas covered by floating ice." It was only after two years that the technology was first used. This invention, therefore, clearly represents an important technological advancement available with delay.

3 Data, Bayesian VAR, and Identification Procedure

The information set contains a combination of technology, real macroeconomic, and forward-looking variables, described in Appendix A. We estimate our benchmark VAR model with 10 endogenous variables. All variables except inflation (reported in annualized percent) are in log levels as in Barsky and Sims (2011), allowing for the possibility of cointegration among them.

[16]In 1986, the Japanese company Nikon introduced a prototype of the first digital single-lens reflex (DSLR) camera, the Nikon SVC. The information contained in Kodak's patent was very important for this development.

The data frequency is quarterly, from 1961:Q1 to 2010:Q4 and the model contains four lags and an intercept term. We employ a Bayesian VAR in order to deal with the large number of coefficients by taking advantage of Minnesota priors (Litterman, 1986; Bańbura et al., 2010). Confidence bands for the impulse response graphs are computed using 1,000 draws from the posterior distribution.

The patent-based news shock is identified following the procedure introduced by Francis et al. (2014) and the maximum forecast error variance approach in Uhlig (2005), which was further developed by Barsky and Sims (2011).

Taking a vector of endogenous variables $\mathbf{y}_t$, assuming that patent-based innovation index is ordered first, the moving average representation (in levels) is written as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{1}$$

If there is a linear mapping of the innovations ($\mathbf{u}_t$) and the structural shocks ($\mathbf{s}_t$), this moving average representation can be rewritten as

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \tag{2}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{3}$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}_0$, $\mathbf{s}_t = \mathbf{A}_0^{-1}\mathbf{u}_t$, and $\mathbf{A}_0$ is the impact matrix that makes $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$ (variance-covariance matrix of innovations). It is possible to rewrite $\mathbf{A}_0$ as $\tilde{\mathbf{A}}_0\mathbf{D}$, where $\tilde{\mathbf{A}}_0$ is the lower triangular Cholesky factor of the covariance matrix of reduced-form innovations (or any other orthogonalization), and $\mathbf{D}$ is any $k \times k$ matrix that satisfies $\mathbf{D}\mathbf{D}^{'} = \mathbf{I}$.

Considering that $\Omega_{i,j}(h)$ is the share of the forecast error variance of variable i of the structural shock j at horizon h, and that patent-based innovation index is driven only by one exogenous shock (patent-based news shock), it follows that $\Omega_{1,1}(0)_{news} = 1$, where $h = 0$ refers to the effect on impact, $i = 1$ refers to patent-based index and $j = 1$ is the patent-based news shock. The share of the forecast error variance of the patent-based news shock is defined as

$$\Omega_{1,1}(0)_{news} = \frac{\mathbf{e}_1^{'}\left(\mathbf{B}_\tau\tilde{\mathbf{A}}_0\mathbf{D}\mathbf{e}_2\mathbf{e}_2^{'}\mathbf{D}^{'}\ \tilde{\mathbf{A}}_0^{'}\mathbf{B}_\tau^{'}\right)\mathbf{e}_1}{\mathbf{e}_1^{'}\left(\mathbf{B}_\tau\mathbf{\Sigma}\mathbf{B}_\tau^{'}\right)\mathbf{e}_1} = \frac{\mathbf{B}_{1,\tau}\tilde{\mathbf{A}}_0\ \gamma\gamma^{'}\tilde{\mathbf{A}}_0^{'}\mathbf{B}_{1,\tau}^{'}}{\mathbf{B}_{1,\tau}\mathbf{\Sigma}\mathbf{B}_{1,\tau}^{'}}, \tag{4}$$

where $\mathbf{e}_1$ is a selection vector with 1 in the position $i = 1$ and zeros elsewhere, $\mathbf{e}_2$ is a selection vector with 1 in the position $i = 1$ and zeros elsewhere, and $\mathbf{B}_\tau$ is the matrix of moving average coefficients measured at each period until τ. Since the effect of interest here is on impact, this can be simplified as $\tau = 0$. The combination of selection vectors with the proper column of $\mathbf{D}$ can be written as γ, which is an orthonormal vector that makes $\tilde{\mathbf{A}}_0\gamma$ the impact of a news shock over the variables.

The patent-based news shock is identified by solving the optimization problem

$$\gamma = argmax\ \Omega_{1,1}(0)_{news}, \tag{5}$$

s.t.

$$\gamma'\gamma = 1, \tag{6}$$

where the restriction imposes that the γ vector is orthonormal.

In summary, the patent-based news shock is identified as the shock that best explains unpredictable movements of the patent-based innovation index on impact ($h = 0$). This is equivalent to finding the linear combination of the reduced-form VAR innovations u_t that maximizes the forecasting variance of productivity on impact.[17]

4 Results

In this section we discuss the effects of our patent-based news shock on the business cycle. We discuss its effect on aggregate productivity as well as on the following macroeconomic variables: output, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index. We then provide industry evidence and document which industries prove to be most relevant for our results. We consider a horizon of five years (20 quarters) which, as suggested by Barsky et al. (2015), represents a reasonable benchmark horizon for predictions of future productivity. In addition, this is the horizon over which the effect of the patent-based news shocks on patent-based innovation index dies out.

4.1 Patent-Based News Shocks and Total Factor Productivity

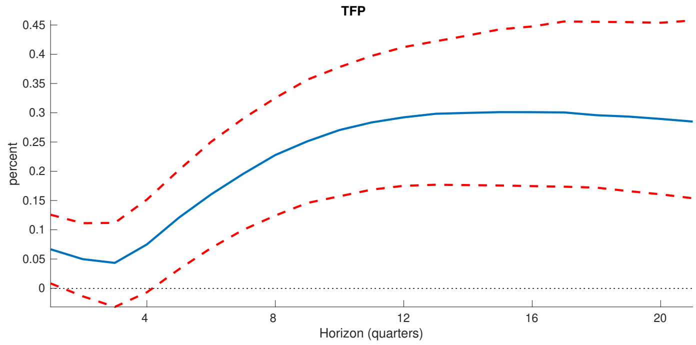
Figure 5 displays the response of TFP to a patent-based news shock described above. Even though the impact response of TFP is *not* restricted, it is barely statistically different from zero. After this small initial jump, TFP decreases for about a year before it slowly picks up and converges to its new long-run level.[18] However, it is only after about five quarters that the coverage bands of the impulse response do not rule out a zero effect. This result implies that after an announcement of a new patent grant, a jump in the firm's stock price – a forward-looking variable – anticipates the expected future aggregate technological improvements brought by the implementation of this patent. In fact, after a favorable patent-based news shock, TFP permanently increases by about 0.3 percent.

As pointed out by Barsky et al. (2015), a news shock should not be correlated with current productivity but should predict its future movements. The shock we identify does precisely that.

[17] The signs of the identified shocks might flip because the identification is based on the forecast error variance. To ensure a positive patent-based news shock, we check whether the response of the patent-based index is positive on impact. If the response is negative, all computed responses are multiplied by (-1).

[18] This slight decrease of aggregate TFP before it starts to rise might be a reflection of a creative destruction that is documented by KPSS at the firm-level.

Figure 5 Response of TFP to a Patent-Based News Shock



Note: The blue solid line is the estimated impulse response to a patent-based news shock and corresponds to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the patent-based innovation index, TFP, GDP, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index. The time period is from 1961:Q1 to 2010:Q4. The system is estimated in the levels of all variables, features four lags and a constant. The dashed red lines represent +/- one standard deviation confidence bands of the patent-based news shock obtained by drawing from the posterior.

The above result suggests that an innovation in the patent-based index carries information about aggregate productivity many periods into the future but not about its current level. This conclusion is bolstered by the fact that the patent-based index Granger causes future productivity and that there is significant correlation between the current level of the patent-based index and TFP five years ahead, while there is no correlation in the short run.[19]

The TFP response presented in Figure 5 also resembles a process that follows a slow diffusion of new innovative activity, as discussed by Portier (2014). In particular, in line with the illustrative examples provided above, the author argues that a "true" technological news shock should take some time to diffuse into aggregate productivity. As a result, impulse responses of TFP after a news shock should not show a significant increase in the short-run.[20] Barsky and Sims (2011), for example, have trouble reproducing this fact even after imposing a zero-impact response of TFP. Figure B1 in the Appendix displays responses of TFP to a news shock identified using four different identification schemes often used in the literature. It is clear that when zero-restrictions are not imposed the response of TFP on impact is quite large (about 0.7 percent and 0.2 percent when Barsky and Sims, 2011, and Francis et al., 2014, identification without zero impact restriction is used, respectively), making the results less compatible with the diffusion news story. In addition, these results show that TFP may not be a perfect measure of technology and that it might be problematic to explore features of this particular series to extract news shocks.

[19]A Granger causality test reveals that movements in the patent-based index predict movements in TFP. The value of the F statistic is 7.89 with a p-value of .0001 for a lag length of 3 chosen according to the Bayesian Information Criterion.

[20]In particular, the response of TFP in Figure 5 very much resembles a response to a hypothetical news shock in panel (d) of Figure 2 in Portier (2014). Using Portier's terminology, our patent-based news shock very much resembles a diffusion news shock.

In light of these results, the attractive feature of our identification is that it does not rely on imposing any assumptions about short- and long-run behavior of TFP. Our results are not affected by the measure of TFP used. Traditionally, news literature uses utilization-adjusted TFP as a proxy for the technological level of the economy, which we also adopt as our benchmark case. However, as Figure B2 in the Appendix illustrates, the responses to a patent-based news shock are almost identical regardless of whether productivity is adjusted for capacity utilization. Furthermore, as evident from the right panel of this figure, our patent-based news shock essentially represents an unexpected innovation to the patent-based index.

Finally, as an additional check, we perform a local projection of the patent-based news shock on utilization-adjusted TFP, following methodology proposed by Òscar Jordà (2005). As presented in Figure B3 in the Appendix, the response of TFP is zero on impact, and starts to slowly increase over time. After 20 quarters it is statistically different from zero. This robustness test provides extra evidence of the power of the patent-based news shock on capturing the technological diffusion characterized by the news shock literature.[21]

4.2 Patent-Based News Shock and Business Cycle

Figure 6 shows the responses of output, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index to a positive patent-based news shock.

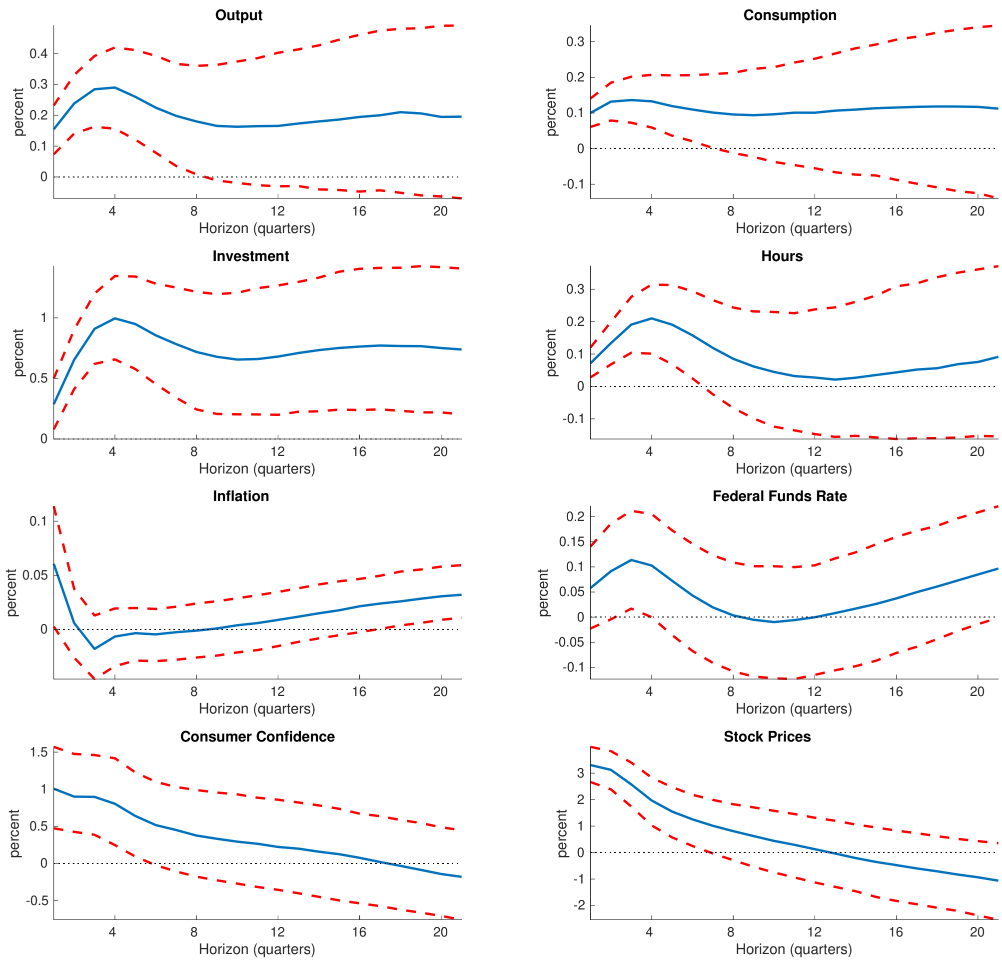
A patent-based news shock induces a clear comovement among output, consumption, investment, and hours. Output increases by about 0.15 percent on impact. Interestingly, much of this increase is dictated by investment behavior. In particular, the 0.25 percent impact response of investment is higher than that of output. The effect is long-lasting as investment remains positive at a new higher level of about 0.7 percent. Consumption also reacts positively on impact, but this effect is quite muted, with an impact increase of about 0.1 percent. This new higher level is sustained even after five years, but the coverage bands do not rule out a zero long-run effect. The response of hours is positive on impact and through about seven quarters.

Output, consumption, investment and hours all rise on impact and display hump-shaped responses. The majority of these movements happen even before the positive effect on TFP becomes significant and TFP starts picking up, which is clearly indicative of the identified shock carrying advance information about future productivity prospects, rather than tracking its path. The strong positive impact effect on two forward-looking variables, stock prices and consumer confidence, also confirms the anticipation feature of the patent-based news shock. This result suggests that economic agents anticipate future technological improvements and act upon them before actual changes in TFP materialize.

The impact responses of inflation and the federal funds rate are particularly interesting.

[21] Local projections of the patent-based news shock on other macroeconomic variables are qualitatively similar to the ones presented on Figure 6 and are available upon request.

Figure 6 Responses to a Patent-Based News Shock



Note: The blue solid lines are the estimated impulse responses to a patent-based news shock, and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the patent-based innovation index, TFP, GDP, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index. The time period is from 1961:Q1 to 2010:Q4. The dashed red lines represent +/- one standard deviation confidence bands of the patent-based news shock obtained by drawing from the posterior.

Both inflation and the federal funds rate rise mildly on impact, although the response of the federal funds rate does not rule out a zero effect. The positive response of the federal funds rate is in line with the initial increase in inflation, and with the predictions of a standard New Keynesian model. However, most of the empirical news shock literature suffers from a so-called disinflation puzzle, a negative and persistent response of inflation to a positive news shock (see, for example, Barsky and Sims, 2011; Kurmann and Sims, 2017; Barsky et al., 2015). As pointed out by Barsky and Sims (2009), in order to make these empirical findings consistent with a New Keynesian model, one would need to account for additional features, such as exogenous real wage rigidity or monetary policy that reacts to output growth rather than output gap. In addition, Jinnai (2013) shows that if capital is added into the model, additional modifications

Table 1 Distribution of the Forecast Error Variance

horizon	TFP			Output			Consumption			Investment		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.2	1.4	4.2	0.8	3.3	7.2	1.7	4.3	8.1	0.2	1.7	4.9
4	0.5	1.7	5.0	2.3	6.7	12.2	1.5	4.5	9.5	4.1	9.3	15.0
8	2.0	6.0	12.7	1.7	5.2	11.1	1.1	3.2	7.9	3.5	8.8	15.4
16	5.8	15.7	26.1	1.7	4.7	11.2	0.9	2.7	7.8	3.7	9.3	18.1
20	6.9	17.8	29.0	1.7	4.8	11.8	0.9	3.0	8.1	4.0	10.1	20.0
horizon	Hours Worked			Inflation			Consumer Confidence			Stock Prices		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.4	1.9	4.9	0.1	0.6	2.8	0.7	3.0	7.1	13.8	20.6	27.6
4	1.3	4.3	8.8	0.4	1.7	5.2	1.2	3.7	8.5	8.1	13.6	20.8
8	1.1	2.9	7.1	0.8	2.2	5.5	1.3	3.7	8.7	5.6	10.0	17.0
16	1.1	2.7	6.9	1.1	3.0	7.1	1.7	4.3	9.3	4.9	8.4	13.4
20	1.1	2.9	7.7	1.5	3.7	8.0	1.9	4.7	9.6	4.8	8.4	13.4

Note: The table reports distribution of forecast error variance explained by a patent-based news shock at different horizons – namely at 0, 4, 8, 16, and 20 quarters.

such as sticky nominal wages in the labor market and a monetary policy that responds to consumption growth rate are needed. Our results show that all these additional features are not needed in the first place.

Table 1 displays the distribution of forecast error variance explained by the patent-based news shock. There are several compelling observations. First, the shock explains almost no short-run variations in TFP, while it accounts for a large part of the longer-run variations in TFP. Recall that our identification procedure does not impose this result as it is the case with identifications based on forecast error maximization of TFP. This result is encouraging, because it suggests that the information contained in firms' stock prices after they have been granted the patent clearly explains part of future TFP movements. Furthermore, this result does not come as a surprise given our previous assertion regarding the patent-based index Granger causing TFP and patent-based index being significantly correlated with TFP only after about 20 quarters.

Second, the patent-based news shock explains about 9 to 10 percent of the variation in investment in the long run, and about 5 to 7 percent of output (mean of the posterior distribution). Interestingly, the identified shock explains variations in output and investment at horizons when positive changes in TFP have not materialized or reached their long-run level, in line with the idea of anticipated effects from future technological improvements.

Third, the shock explains a large part of short-run variation in stock prices. In particular, it explains about one-fifth of total variation on impact and less than one-tenth of total variation after five years. This result is in line with news being reflected immediately in forward-looking variables, with a diminishing effect over time, and with stock market efficiency. The shock accounts only for 3 to 5 percent of the variation of consumer confidence, at all horizons.

Overall, our results indicate that the patent-based news shock explains a large part of longer-run variations in TFP, suggesting that it carries relevant information about future productivity movements. This shock also induces comovement among output, consumption, investment and hours. Furthermore, contrary to technological news shocks identified by maximizing variations in TFP, patent-based news shocks induce responses of inflation and the federal funds rate in line with the New Keynesian model.

It is important to note that our results are likely to understate the effects of news shocks. KPSS use patents from publicly listed firms and therefore do not cover the universe of all patented innovations. Although this effect is minimized by constructing the aggregate index as we discussed above, not all innovations are patented in the first place, as patenting is a strategic decision. Therefore, our results are likely to represent a lower bound on the (business cycle) importance of true news shocks. The fact that patent-based news shock still explains quite a good share of variations in TFP is reassuring because it suggests that the shock we identify carries important information about future productivity.

4.3 Industry Evidence

The aggregate patent-based innovation index is based on the valuations of patents spanning many different industries. To better understand which industries technological news originate from, we break up the aggregate index into indexes specific to nine SIC divisions: 1) Agriculture, Forestry and Fishing, 2) Construction, 3) Finance, Insurance and Real Estate, 4) Manufacturing, 5) Mining, 6) Retail Trade, 7) Services, 8) Transportation, Communications, Electric, Gas and Sanitary service, and 9) Wholesale Trade. We disaggregate the divisions that turn out to be crucial further into industries and subindustries. For each major division (and relevant industries) we construct a patent-based innovation index following the same procedure as with the aggregate index, i.e. summing the valuations of all patents from that particular division (industry). We then repeat the same exercise as in the previous two subsections, replacing the aggregate index with a division (industry) index.

Our industry evidence suggests that patenting activity in manufacturing is most relevant for explaining observed aggregate movements. Within manufacturing, the most important industries are *Electronic and Other Electrical Equipment and Components, Except Computer Equipment* (electronic/electrical), followed by *Industrial And Commercial Machinery And Computer Equipment* (machinery), and *Chemicals And Allied Products* (chemicals).[22] These three industries account for 63% of the total number (and 64% of the total value) of all patents in Manufacturing.[23]

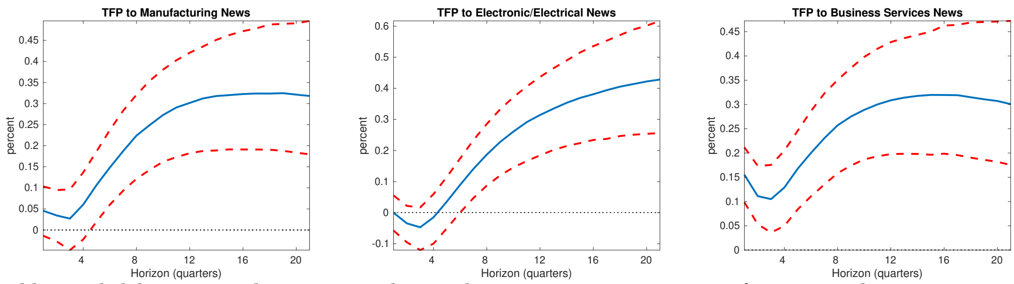
Figure 7 displays the responses of aggregate productivity to a positive shock to the manufacturing patent-based index (left panel) and to the electronic/electrical patent-based news

[22]This result is in line with Vukotić (2019) who shows that aggregate news shocks propagate mainly through the durable goods industries within manufacturing.

[23]Electronics account for 29% (number) and 22% (value), machinery for 17% (number) and 20% (value), and chemicals account for 17% (number) and 28% (value) of all patents in manufacturing.

shock (middle panel). In both cases, aggregate TFP does not increase on impact, takes time to become significant, and converges to a new higher value. This pattern is somewhat more pronounced when only patents in electronic/electrical are considered. In particular, TFP takes almost two years to become significantly different from zero, then slowly converging to a higher value, 0.4. Notice that this increase is higher than when all patents in the sample are considered. This result suggests that the patenting activity in manufacturing, and in electronic/electrical in particular, carries important information about future movements in the aggregate TFP. This assertion is confirmed by looking at the FEV of TFP due to these two shocks, which is displayed in Table 2; the manufacturing news shock explains 19%, and the electronic/electrical news shock explains 25% of the FEV of TFP after 20 quarters.

Figure 7 Effects of Disaggregated Patent-Based News Shocks on TFP



Note: The blue solid lines are the estimated impulse responses to a manufacturing division patent-based news shock (left panel), an electronic/electrical industry patent-based news shock (middle panel), and a business services industry patent-based news shock (right panel). The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the manufacturing patent-based innovation index (left panel), the electronic/electrical patent-based innovation index (middle panel), the business services patent-based innovation index (right panel), and TFP, GDP, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index in all three panels. The time period is from 1961:Q1 to 2010:Q4. The dashed red lines represent +/- one standard deviation confidence bands obtained by drawing from the posterior.

Appendix C presents the responses of other macroeconomic variables to these shocks. The responses are even more pronounced than in the case of the benchmark aggregate patent-based news shocks, as can be seen in Figure C1. The same pattern holds with the FEV of output, consumption, investment, and hours, as shown in Table C1. The most interesting result is that the electronic/electrical patent-based news shock explains large portions of the FEV of output (18% after 20 quarters), consumption (23% after 20 quarters), investment (28% after 20 quarters), and hours (12% after 20 quarters). Patenting activity in these few industries, therefore, proves to be crucial not only for explaining future movements in TFP, but also in other macroeconomic variables.

The most relevant subindustry within the electronic/electrical industry is *Semiconductors and Related Devices*; this subindustry accounts for 25% of the total number (and 35% of the total value) of all patents in electronic/electrical. In addition, it accounts for 70 out of top 100 valued manufacturing patents. All of these 70 patents belong to Cisco. Other companies that dominate patenting in this industry are Intel, Dell, and Apple; top patents in machinery are

Table 2 Distribution of the Forecast Error Variance of TFP

	Manufacturing Patent-Based News			Electronic/Electrical Patent-Based News			Business Services Patent-Based News		
horizon	TFP			TFP			TFP		
	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.1	0.5	1.9	0.0	0.3	1.2	1.7	4.3	7.8
4	0.4	1.3	3.9	0.4	0.2	2.5	1.7	4.8	9.4
8	2.1	6.0	12.7	2.1	4.6	9.4	4.3	10.3	18.0
16	6.8	16.7	27.4	8.4	19.4	30.7	8.8	19.3	30.2
20	8.2	19.3	30.8	11.9	25.1	38.7	9.7	21.2	32.3

Note: The table reports distribution of forecast error variance of TFP explained by the manufacturing division patent-based news shock, by the electronic/equipment industry patent-based news shock, and by the business services patent-based news shock at different horizons – namely at 0, 4, 8, 16, and 20 quarters.

dominated by EMC Corporation, while top patents in chemicals are dominated by Pfizer.

Another division that proves to be relevant for explaining movements in the aggregate TFP is Services, with Business Services representing 93% of all services patents. In what follows we show the results considering only business services patent-based news shocks.

The right panel of Figure 7 displays the response of the aggregate TFP to the business services patent-based news shock, while the right panel of Table 2 displays the FEV of TFP explained by this shock. TFP significantly increases on impact, but follows a similar shape as in the case of manufacturing and electronic/electrical news; it slowly decreases after the initial impact before approaching a new higher level, 0.3. The shock explains about 5% of short-run movements in TFP and about 21% after 20 quarters.

The reason why TFP jumps on impact most likely related to the nature of patents in this industry. In particular, the most relevant subindustry is *Computer Programming, Data Processing, And Other Computer Related Services* which accounts for 80% of the total number of patents in business services. The companies that lead the way in this subindustry are Microsoft, accounting for 32%, and Oracle, accounting for 11% of the total value of patents. Therefore, it is highly likely that most patents that are closely related to programming and data processing get implemented much faster than manufacturing patents, where sophisticated products/processes take longer to bring to the market. This result also explains why the aggregate shock induces a mild, although barely significant, positive effect on TFP on impact, as shown in Figure 5.

5 Discussion

In this section we investigate how our patent-based news shock compares to news shocks identified using methods based on maximizing the variance decomposition of TFP and with shocks to widely used forward-looking variables, consumer confidence and aggregate stock price index.

5.1 Relation to TFP-Based News Shocks

While patent-based news shocks are likely to represent a lower bound of the importance of true news shocks, the shocks identified using maximum variance decomposition of TFP are likely to represent an upper bound. It is, therefore, worth discussing the difference between them.

As pointed out by Barsky and Sims (2011), other structural shocks that can affect productivity in the future and not immediately, such as research and development shocks, investment-specific shocks, or re-allocative shocks, would be confounded with true news shocks when maximum variance decomposition of TFP is used, thus misrepresenting the importance of news shocks in driving the business cycle. This is not the case with our identification method, as we do not use TFP to identify the shock and only concentrate on unexpected movements in values of patents after they are granted.

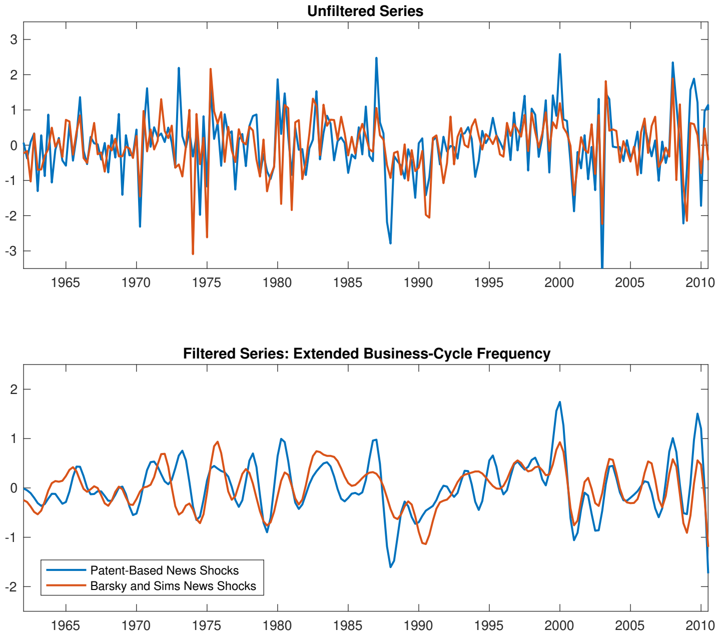
In addition, Barsky et al. (2015) and Sims (2016) indicate that the variance decomposition is likely to overstate the effects of news shocks. In particular, to isolate the independent contribution of "pure" news shocks, one has to separate movements due solely to expected changes in fundamentals from movements due to change in fundamentals when the anticipated change actually occurs. For example, using a DSGE model setting as in Schmitt-Grohé and Uribe (2012), Sims (2016) shows that "pure" news shocks explain between 2 and 9 percent of the variance of the level of output at business cycle frequencies, whereas "realized" news shocks explain between 20 and 40 percent. Furthermore, using a SVAR approach, Barsky et al. (2015) document that responses of consumption, investment, and hours are cut roughly in half when only the "pure" news component is isolated.

Our results are less susceptible to this criticism, because the response of TFP to a patent-based news shock unconditionally resembles a slow diffusion process. This path is in line with the concrete examples we presented before. The slow technology diffusion induced by a patent starts with the patent grant and public disclosure of the information contained therein, with next movers commonly using this information and applying it to develop new products or processes. A release of a patent, therefore, can be thought of as representing a basis for subsequent patented and nonpatented technological improvements.

Nevertheless, it warrants to directly compare our recovered patent-based news shock with the most commonly used TFP-based news shock – the news shock identified using the identification proposed by Barsky and Sims (2011).

The top panel of Figure 8 displays the two series and they appear to be quite correlated. We confirm this assertion in Table 3 (row 1): the correlation between patent-based news shocks and Barsky and Sims news shocks is 0.61. Given that Barsky and Sims' TFP-based identification scheme maximizes FEV of TFP *over* 40 quarters, we isolate two components of the economic cycle, a high-frequency component (fluctuations between 2 and 6 quarters) and an extended business-cycle frequency component (fluctuations between 6 and 40 quarters); this decompo-

Figure 8 Patent-Based News Shocks vs TFP-Based News Shocks



Note: The top panel displays unfiltered series of patent-based news shocks and news shocks arising from the identification proposed by Barsky and Sims (2011). The bottom panel represents the same two series filtered at extended business-cycle frequency (fluctuations between 6 and 40 quarters). The cyclical component is isolated using the band-pass filter.

sition helps us to understand the degree of comovement between the two series at different horizons.[24] In the bottom panel of Figure 8 we display the extended business-cycle frequency component of the two series.

When cleaned from high frequency fluctuations the two series appear to be even more correlated. This can be more formally seen in Table 3 (rows 2 and 3) where we report correlations at different components of the cycle; the correlation between our patent-based news shocks and Barsky and Sims news shocks at extended business-cycle frequency amounts to 0.70. This result is quite encouraging considering that our identification strategy does not rely on any maximization of FEV of TFP at any horizon, yet it is lower frequencies at which it seems to be more correlated with the series that, by definition, focuses both on high and low frequencies.

These results further confirm that our procedure picks up shocks that are closely related to future improvements in technology, but overcoming criticisms of widely used TFP-based identification schemes at the same time.

[24]Instead of using business-cycle frequency as usually defined in the literature as fluctuations between 6 and 32 quarters, we include fluctuations of up to 40 quarters to account for the horizon used in the TFP-based identification.

Table 3 Correlation of Patent-Based News Shocks with TFP-Based News Shocks at Different Frequencies

Frequency	Barsky and Sims News Shocks
Unconditional	0.61
High-Frequency, 2-6 quarters	0.56
Extended Business-Cycle Frequency, 6-40 quarters	0.70

Note: The table reports correlations, at different frequencies, of patent-based news shocks with news shocks arising from the identification proposed by Barsky and Sims (2011). The cyclical component is isolated using the band-pass filter.

5.2 Relation to Innovations in Forward-Looking Variables

The necessity of using forward-looking variables to capture agents' expectations about future developments in economic activity, and TFP in particular, has been well recognized in the news literature. For example, Beaudry and Portier (2006) focus on a surprise shock to the aggregate stock price index that is orthogonal to innovations in TFP, and they show that it explains a large portion of business cycle fluctuations. Using different approaches, Barsky and Sims (2012) and Barsky et al. (2015) claim that an innovation to consumer confidence to a large extent represents a technological news shock.

Considering these results, we compare responses to our patent-based news shock with shocks that explain the most impact variations in two aggregate forward-looking variables: stock prices and consumer confidence.[25] We refer to these two shocks as stock price shock and consumer confidence shock, respectively.

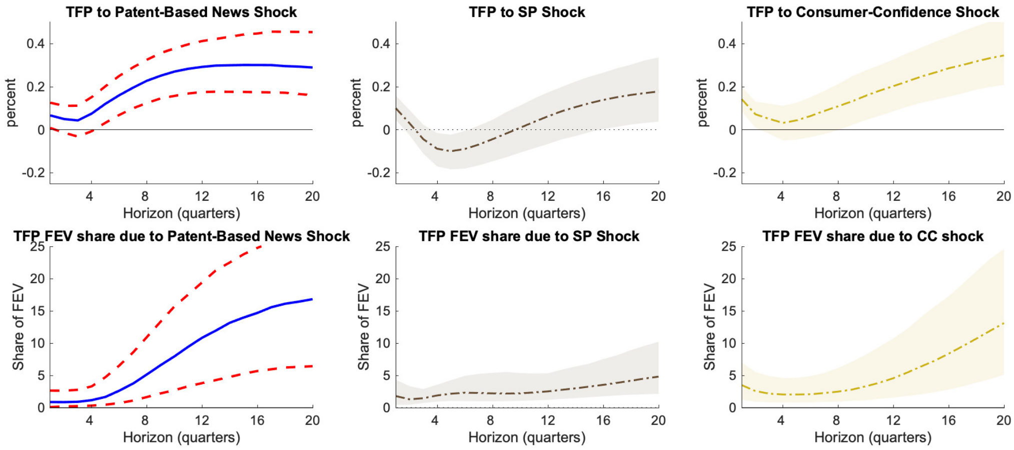
Stock price index and consumer confidence are likely to reflect beliefs about economic fundamentals in general, and not only about future technological prospects. As discussed earlier, movements in these two forward-looking variables, and especially in consumer confidence, might also reflect autonomous fluctuations in beliefs not related to economic fundamentals, such as sentiment and animal spirits.[26] Below we provide some indicative evidence in support of this assertion.

We argue that fluctuations in the stock market value of the firms in a short time period around the patent grant date are less susceptible to this criticism and, therefore, are more likely to reflect true beliefs about future technological prospects. To this end, the top panel of Figure 9 displays responses of TFP to positive patent-based news, stock price and consumer-confidence shocks. The bottom panel displays the share of TFP's forecast error variance explained by these three shocks, respectively.

[25]We use the same procedure explained in Section 3 to identify stock price shock and consumer confidence shocks. Namely, we order stock price (consumer confidence) first in the VAR composed of the same 10 variables as above and recover the shock that maximizes the forecast error variance of the stock price (consumer confidence).

[26]This literature usually views these autonomous fluctuations as having a causal effect on economic activity and the business cycle. See, for example, Barsky and Sims (2012), Angeletos and La'O (2013), Benhabib et al. (2015), Angeletos et al. (2018) and Levchenko and Pandalai-Nayar (2018).

Figure 9 Response and Variance Decomposition of TFP to Patent-Based News, Stock Price and Consumer Confidence Shocks



Note: The top panel represents responses of TFP to a patent-based news shock (left), stock price shock (middle) and consumer confidence shock (right). Median responses to a patent-based news shock are represented by blue solid lines, and red dashed lines represent +/- one standard deviation confidence bands. Patent-based innovation index is ordered first in the VAR. Median responses to a stock price (consumer confidence) shock are represented by brown (yellow) dash-dotted line, while the brown (yellow) shaded area represents +/- one standard deviation confidence bands. Stock price (consumer confidence) is ordered first in the VAR. The bottom panel represents a corresponding forecast error variance share of TFP due to a patent-based news shock (left), stock price shock (middle) and consumer confidence shock (right). The time period is from 1961:Q1 to 2010:Q4.

Two observations regarding the TFP's behavior in response to these three shocks stand out.

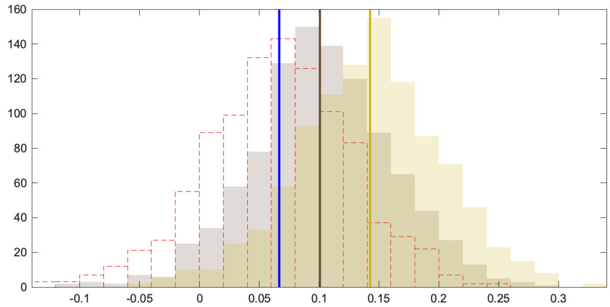
First, the coverage bands of the impact response to a patent-based news shock do not rule out a zero effect, and this is almost unchanged during the first year after which TFP slowly starts to take off. TFP raises mildly in response to a stock price shock and quite significantly in response to a consumer confidence shock. To illustrate this point further, in Figure 10 we show the whole distribution of the effect on impact on TFP after these three shocks. The median effect of the patent-based news shock is closer to zero than the stock price and the consumer confidence shocks. It is also clear that the distribution generated by the patent-based news shock incorporates zero, and, in the case of the other two shocks, the zero outcome seems to be a tail event.

Second, the forecast error variance decomposition reveals that it is the patent-based news shock that explains the largest share of the variance of TFP after a five-year period. This result, together with the fact that the patent-based index Granger causes TFP as documented above, is suggestive that the information contained in the patent-based index is an important force behind the TFP diffusion.

The responses of other macroeconomic variables that we considered previously are displayed in Figure 11. Output, consumption, investment and hours overall respond more to a stock price shock, and to a consumer confidence shock in particular, than to a patent-based news shock. The effect of consumer-confidence shock is the longest lasting.

We believe that these results are supportive of our previous assertion. First, larger responses

Figure 10 Distribution of TFP Impact Response to Patent-Based News, Stock Price and Consumer Confidence Shocks



Note: Distribution of TFP impact response to a patent-based news shock (white area with red-dashed borders), stock price shock (shaded brown area), and consumer confidence shock (shaded yellow area). Blue, brown, and yellow vertical lines correspond to a median of the distribution in the case of patent-based news, stock price, and consumer confidence shocks, respectively. Histograms constructed over all 1,000 posterior draws. The time period is from 1961:Q1 to 2010:Q4.

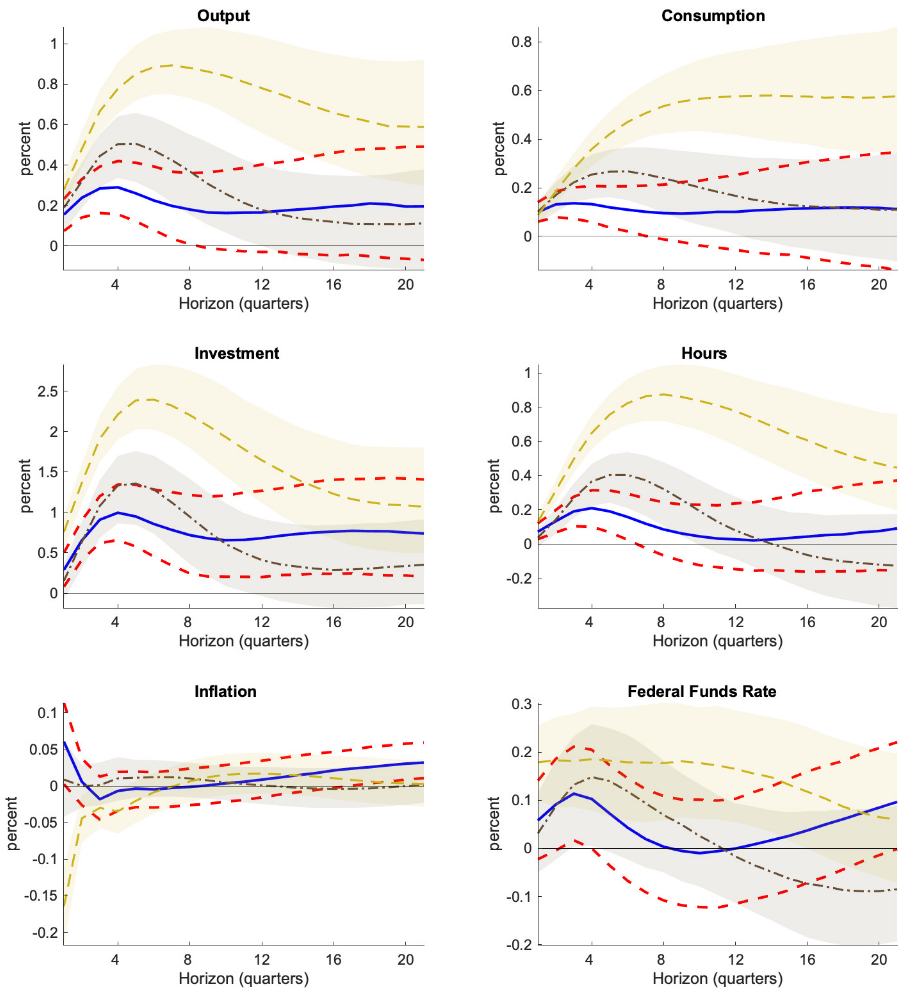
of output, consumption, investment and hours to stock price and consumer confidence shocks, in particular, are somewhat expected given that they are potentially capturing beliefs about broad future economic prospects as well as sentiments or animal spirits. Second, it is harder to infer that innovations to these two forward-looking variables represent *technological* news shocks when they explain a much smaller part of TFP variations than a patent-based news shock, and yet larger variations of these macroeconomic variables. This observation is quite telling. If the shock was truly about future variations in productivity, then one would expect that this shock explains at least as much, if not more, variations in TFP than the patent-based news shock. The stock price index is a much broader index than the patent-based index, yet it elicits only a small increase in TFP and a much larger increase in other macroeconomic variables, suggesting that it is picking up shocks that are not necessarily technological in nature.

6 Robustness: Patent-Based Innovation Index as an Instrument

In this section we perform a robustness check by identifying the patent-based news shock under an alternative methodology. As discussed in Section 2, the patent-based index should be directly linked to what is theoretically considered a technological news shock. The idea here is to employ the proxy VAR procedure introduced by Stock and Watson (2012) and Mertens and Ravn (2013) to identify the patent-based news shock by relying on the patent-based innovation index series as an instrument, which is a noisy measure of the structural shock. In summary, the procedure consists of regressing the instrument against the residuals of a reduced-form VAR and using this information to infer the contemporaneous impact of the patent-based news shock on the macroeconomic variables.

The use of exogenous variables as instruments has been applied by the business cycles liter-

Figure 11 Responses to Patent-Based News, Stock Price and Consumer Confidence Shocks



Note: The figure displays original responses of output, consumption, investment, hours, inflation, and the federal funds rate to a unit patent-based news shock, together with responses to a 1 percent unexpected innovation in aggregate stock price index (dash-dotted brown lines correspond to the posterior median estimates, with the shaded area representing +/- one standard deviation confidence interval obtained by drawing from the posterior) and to a 1 percent unexpected innovation in consumer confidence (dashed yellow lines, with the shaded area representing +/- one standard deviation confidence interval obtained by drawing from the posterior). The responses originate from a VAR composed of the same 10 variables as before, with the patent-based innovation index (with patent-based news shock), stock price (with stock price shock), and consumer confidence (with consumer confidence shock) ordered first. The time period is from 1961:Q1- 2010:Q4.

ature to identify several types of structural shocks.[27] For technological news shocks, Cascaldi-Garcia (2018) employs constructed series of forecast revisions from the Survey of Professional

[27]Some examples are monetary policy shocks (Stock and Watson, 2012; Gertler and Karadi, 2015; Miranda-Agrippino and Ricco, 2018; and Caldara and Herbst, 2019), fiscal policy shocks (Mertens and Ravn, 2014; Caldara and Kamps, 2017), uncertainty shocks (Carriero et al., 2015; Piffer and Podstawski, 2018), oil supply shocks (Montiel Olea et al., 2016), news about future fiscal spending (Auerbach and Gorodnichenko, 2012), and news about future oil supply (Arezki et al., 2017).

Forecasters (SPF)[28] about future GDP, investment, and industrial production as instruments, and Miranda-Agrippino et al. (2019) instrument the structural news shock through the unforecastable component of the number of granted patents filed at the United States Patents and Trademark Office (USPTO).

Two conditions must be satisfied for the applicability of such a series as an instrument: *relevance* and *exogeneity*. The first condition implies that the potential instrument is correlated with the true underlying structural shock. While the true structural shock is not directly observed, this condition cannot be tested. However, the extensive discussion presented in Section 2 makes us confident about the intrinsic relation between the patent-based innovation index and the patent-based news shock.

The second condition of *exogeneity* implies that the potential instrument is not correlated with any other structural shock. We perform here an exogeneity test by calculating the correlation between the patent-based index series[29] and several identified shocks from the literature – namely, news about tax shocks, news about government defense spending, oil price shocks, monetary policy shocks and tax shocks.[30]

The results of the exogeneity tests are displayed in Table 4. The patent-based innovation index is not correlated with oil price shocks and is mildly correlated to news about tax and tax shocks, but these are not statistically significant. With respect to news about government spending and monetary policy shocks, the series is positively correlated, but these are also not statistically significant at a 10% level. Based on these results, we conclude that the patent-based index series passes the exogeneity test and can be used as an instrument in the proxy VAR setup.[31]

We estimate a Bayesian VAR in the same way as described in Section 3, with the exception that now the information set does not include the patent-based index series itself. For each posterior draw of the coefficients, we perform the identification of the patent-based news shock by making use of the proposed instrument. Figure 12 presents the impulse response of the patent-based news shock on TFP. As expected, the patent-based news shock generates a permanent long-run increase in the level of TFP. There is an increase on impact, but this effect rapidly diminishes, in line with the idea of creative destruction. The shape is similar to the one

[28]Calculated by the Federal Reserve Bank of Philadelphia.

[29]We demean the series and control for its lags and lags of utilization-adjusted TFP, in order to ensure that the instrument only contains new information about technology released in time t.

[30]The economic shocks are downloaded from the Caldara and Kamps (2017) database. The measure for news about tax shocks is the proxy calculated by Leeper et al. (2013). News about government defense spending is calculated as the nominal present value of Ramey (2011) defense news variable divided by the nominal GDP of the previous quarter, as calculated by Caldara and Kamps (2017). Oil price shocks are the net oil increase (three years) calculated by Caldara and Kamps (2017) based on Hamilton (2003). Monetary policy shocks are the quarterly sum of the monthly Romer and Romer (2004) variable extended by Barakchian and Crowe (2013). Tax shocks are the Mertens and Ravn (2011) unanticipated tax series.

[31]For comparison, the raw series of the total number of patents presents a correlation with news about tax of negative 0.21 (statistically significant at a 5% level), and of 0.17 with news about government spending (statistically significant at a 10% level). This implies that our measure represents a better instrument for identifying a technological news shock, as the raw number of patents may be confounded with other sources of news.

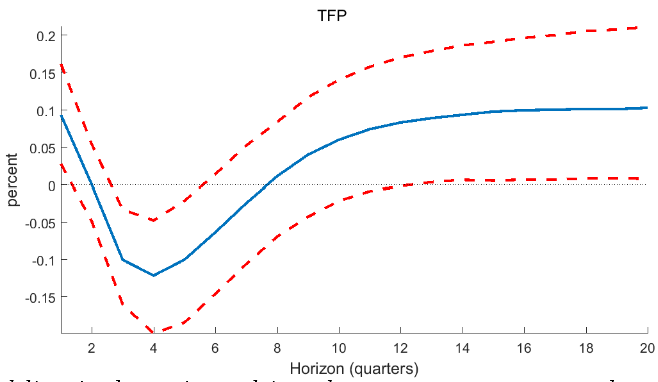
Table 4 Correlations Between the Patent-Based Innovation Index and Selected Shocks

Shock	Source	Correlation	P-value
News about tax	Leeper et al. (2013)	-0.05	[0.717]
News about govt. spending	Ramey (2011)	0.19	[0.102]
Oil price	Hamilton (2003)	0.00	[0.977]
Monetary policy	Romer and Romer (2004)	0.17	[0.102]
Tax	Mertens and Ravn (2011)	-0.08	[0.550]

Note: Values in brackets are p-values for the test of zero correlation under the null hypothesis and are computed by taking into account the false discovery rate of positively dependent tests, following the methodology by Benjamini and Hochberg (1995). Correlations range from 1969:Q1 to 2006:Q3 due to data availability.

presented in Figure 5 identified with our benchmark model.

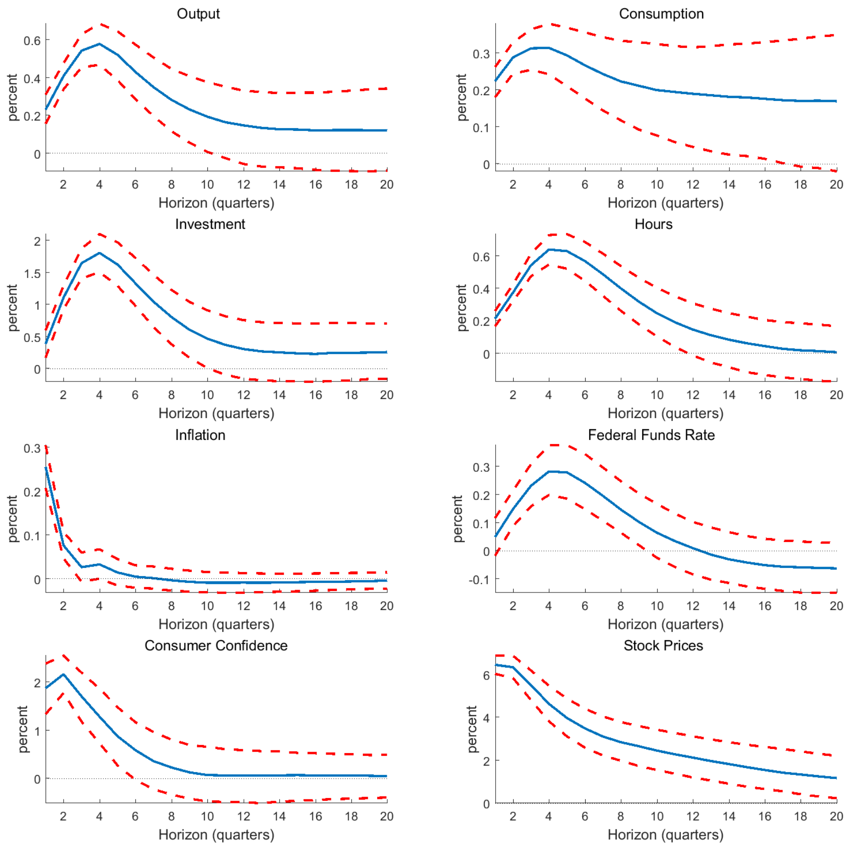
Figure 12 Response of TFP to a Patent-Based News Shock Identified with Patent-Based Innovation Index as an Instrument



Note: The blue solid line is the estimated impulse response to a patent-based news shock identified under a proxy VAR with the patent-based innovation index as an instrument and corresponds to the posterior median estimate. The unit of the vertical axis is the percentage deviation from the situation without a shock. The response originates from a VAR composed of TFP, GDP, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index. The time period is from 1961:Q1 to 2010:Q4. The system is estimated in the levels of all variables, features four lags and a constant. The dashed red lines represent +/- one standard deviation confidence bands of the patent-based news shock obtained by drawing from the posterior.

Figure 13 presents the impulse responses of the other variables included in the information set. All the responses are qualitatively similar to the benchmark model shown in Figure 6. Consumption, investment, and consequently output jump on impact as a response to the expected future technological improvement. Hours worked react positively, converging back to zero in the long run. There is a short-run inflationary effect, which generates the expected increase in the federal funds rate. Consumer confidence and stock prices, as forward-looking variables, jump on impact, anticipating the expected future outcomes of the technological improvement. In summary, these results bring an extra confirmation of the economic effects of the patent-based news shock, in line with the theoretical idea of a neutral technological shock.

Figure 13 Responses to a Patent-Based News Shock Identified with Patent-Based Innovation Index as an Instrument



Note: The blue solid lines are the estimated impulse responses to a patent-based news shock identified under a proxy VAR with the patent-based innovation index as an instrument and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of: TFP, GDP, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index. The time period is from 1961:Q1 to 2010:Q4. The dashed red lines represent +/- one standard deviation confidence bands of the patent-based news shock obtained by drawing from the posterior.

7 Conclusion

This paper contributes to the news literature by exploiting sound microlevel data directly related to technological innovations rather than relying on movements in an imperfect productivity measure such as TFP to extract technological news. In particular, we combine firm-level data on patent grants with the movements in firms' stock prices in response to these grants to identify a plausible technological news shock, which we call a patent-based news shock. We identify the patent-based news shock as the shock that explains most of the contemporaneous variations in the measure that aggregates stock market valuations of all individual patents and argue that it represents an expected future increase in the technology level. The results presented here are also robust to employing the patent-based innovation index as an exogenous instrument for the news shock in a proxy VAR setting.

We show that patent-based news shocks account for about 20 percent of variations in TFP after five years and do not account for any variation in TFP in the short run. In line with the original intuition of Beaudry and Portier (2006), we show that output, consumption, investment and hours all rise on impact, displaying hump-shaped responses. Output movements are dictated more by investment than by consumption behavior, and the effect on investment is more long-lasting than that of consumption. The majority of these movements materialize before the positive effect on TFP becomes significant. Therefore, rather than tracking the path of aggregate productivity, the identified shocks carry advance information about it.

The patent-based news shocks induce a positive effect on impact on two forward-looking variables, stock prices and consumer confidence, which also confirms its anticipation feature. This result suggests that economic agents foresee future technological improvements and act upon them before actual changes in TFP. We show that, contrary to most empirical evidence in the news literature that suffers from a so-called disinflation puzzle, inflation and the federal funds rate both increase on impact in response to our patent-based news shock, consistent with a standard New Keynesian model.

The news shocks identified here explain less of the forecast error variance of main macroeconomic aggregates than typically found in the empirical literature on news shocks. We view our results as representing a lower bound of the importance of technological news shocks given that not all innovative activity is patented in the first place.

Our industry evidence shows that patenting activity in only few industries is predominantly responsible for explaining future movements in TFP. In particular, patenting activity in electronic and electrical equipment industries within the manufacturing sector and computer programming and data processing services within the services sector play a crucial role in driving our results.

Identifying technological news shocks is a difficult task due to the complex process of estimating the aggregate technology level. Exploring microlevel data directly related to innovation is a promising path toward properly measuring the effects of anticipated technological change on the economy. We believe that this paper and the identification of patent-based news shocks represent one important step in that direction.

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Appendix A Data

We use quarterly aggregate data that span the period from 1961:Q1 to 2010:Q4.

The output and hours measure are recovered from the Bureau of Labor Statistics (BLS). The output measure is the log of real output in the nonfarm business sector (BLS: PRS85006043). The hours series is total hours worked in the same sector (BLS: PRS85006033). Both the consumption and investment series are recovered from the Bureau of Economic Analysis (BEA). The consumption measure is the log of real personal consumption expenditures on nondurables and services (BEA Table 1.1.3., sum of lines 5 and 6). The investment series is the sum of real gross private domestic investment (BEA Table 1.1.3., line 7) and personal consumption expenditures on durables (BEA Table 1.1.3., line 4). To obtain per capita values we divide all these series by the BLS series of the civilian noninstitutional population over 16 (LNU00000000Q).

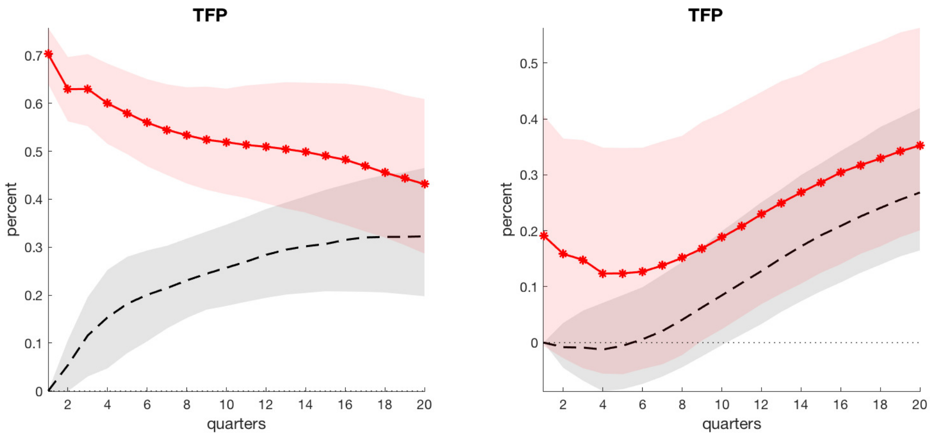
The stock price measure is the log of the Standard and Poor's 500 Composite Stock Price Index, recovered from Robert Shiller's website. The inflation measure is the percentage change in the CPI for all urban consumers (CPIAUCSL, St. Louis FRED). The federal funds rate series is the effective federal funds rate from the Board of Governors (FEDFUNDS, St. Louis FRED). The consumer confidence measure is taken from the Michigan Survey of Consumers as in Barsky and Sims (2011). This series starts in 1961:Q1 and, therefore, dictates the beginning period of our sample.

The TFP measure is the utilization-adjusted measure provided by Fernald (2012).

Appendix B Robustness

B.1 TFP-Based Identification Schemes

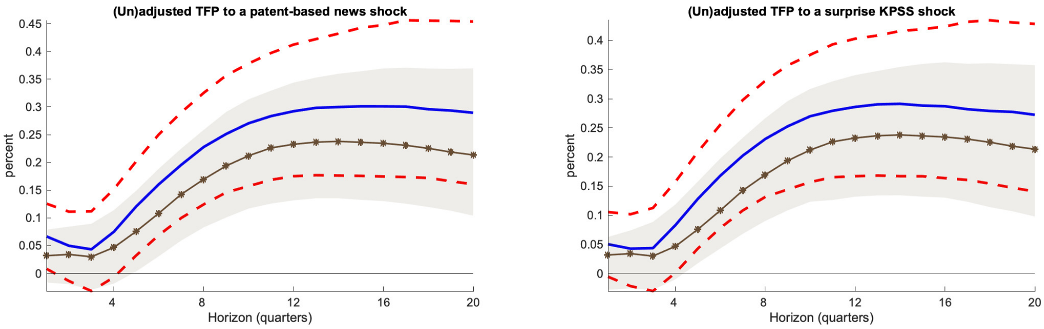
Figure B1 Responses of Utilization-Adjusted TFP to News Shocks



Note: The figure represents estimated impulse responses to a unit TFP-news shock identified using four different identification schemes. The left panel represents responses to a unit news shock identified using the Barsky and Sims (2011) procedure with (black dashed lines) and without zero impact restriction (red dash-starred lines). The right panel represents responses to a unit news shock identified using the Francis et al. (2014) procedure with (black dashed lines) and without zero impact restriction (red dash-starred lines). The time period is from 1961:Q1 to 2010:Q4, the system is estimated in levels of all variables (TFP, GDP, consumption, investment, hours, inflation, the federal Funds rate, consumer confidence, and the stock price index) features four lags and a constant. The shaded areas around the responses represent +/- one standard deviation confidence bands obtained by drawing from the posterior.

B.2 Patent-Based News Shock and Responses of (Adjusted and Unadjusted) TFP

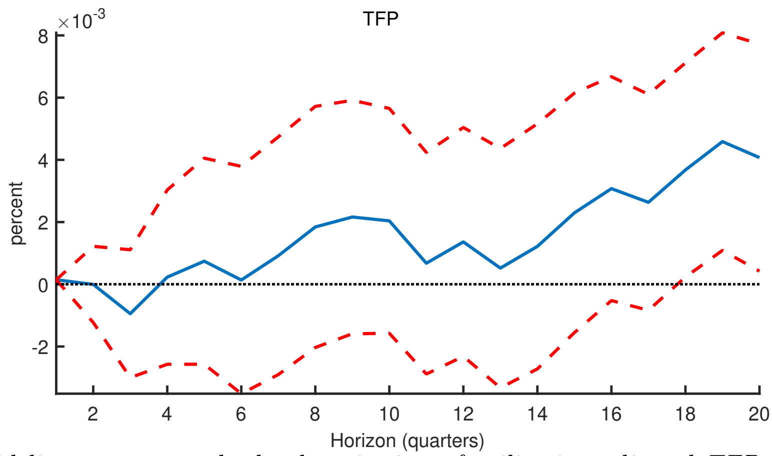
Figure B2 Responses of (Un)adjusted TFP to a Patent-Based News Shock and an Unexpected Shock to the Patent-Based Innovation Index



Note: The left panel represents the response of utilization-adjusted TFP (as in Figure 5 in the main body of the paper) and of unadjusted TFP (dash-starred line) to a patent-based news shock. The right panel represents the response of utilization-adjusted TFP (blue solid line) and of unadjusted TFP (dash-starred line) to an unexpected innovation to the patent-based innovation index. In both panels, the responses originate from a VAR composed of the patent-based innovation index, TFP, GDP, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index. The time period is from 1961:Q1 - 2010:Q4. Shaded areas and dashed red lines represent +/- one standard deviation confidence bands obtained by drawing from the posterior.

B.3 Local Projection of Patent-Based News Shock on Utilization-Adjusted TFP

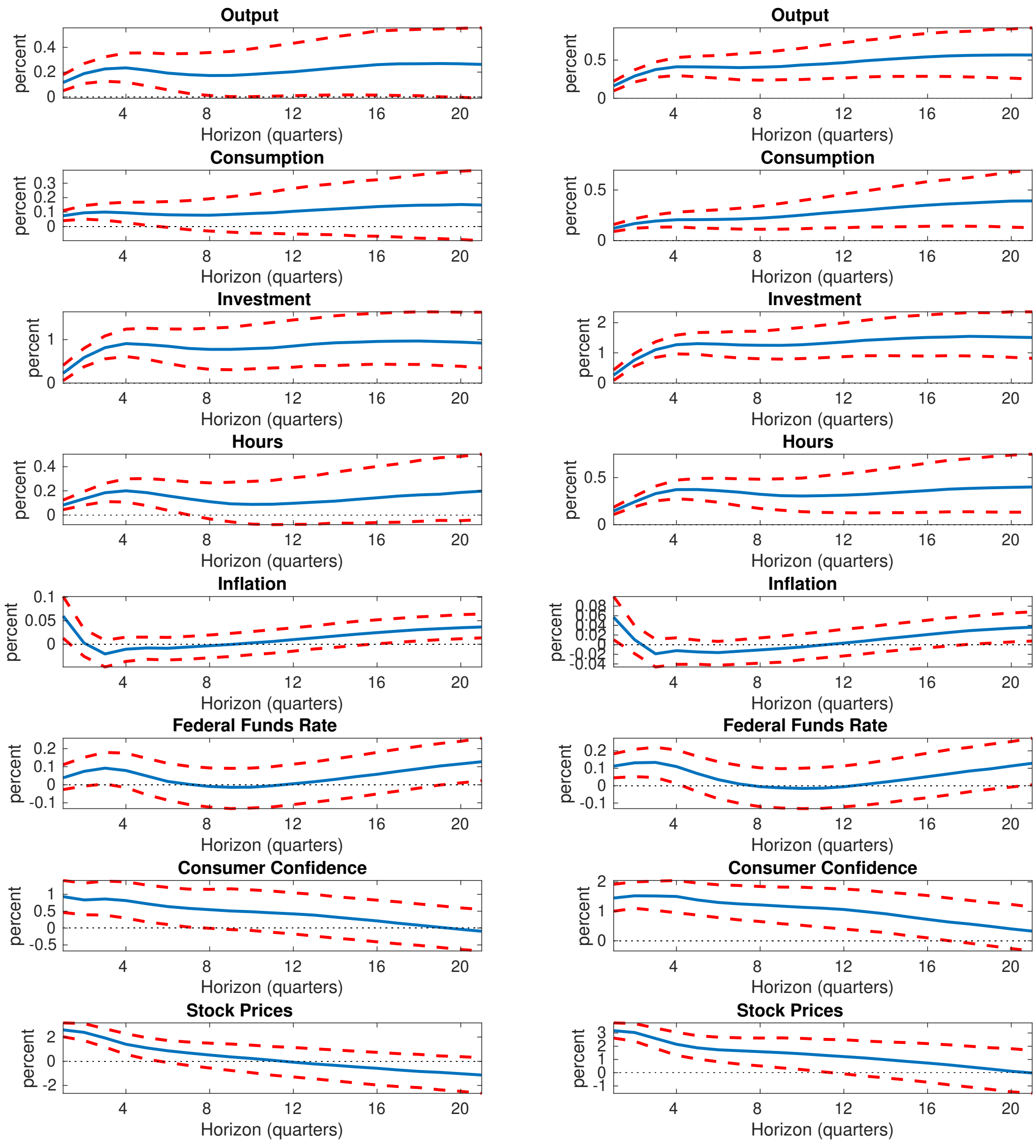
Figure B3 Local Projection of Adjusted TFP to a Patent-Based News Shock



Note: The solid line represents the local projection of utilization-adjusted TFP to a patent-based news shock. The time period is from 1961:Q1 - 2010:Q4. Dashed red lines represent +/- two standard deviations significance bands.

Appendix C Additional Industry Evidence

Figure C1 Responses to Disaggregated Patent-Based News Shocks



Note: The blue solid lines are the estimated impulse responses to a manufacturing division patent-based news shock (left panetl) and to electronic/equipment industry patent-based news shock (right panel), and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the manufacturing patent-based innovation index (left panel) and Electronic/Equipment patent-based innovation index (right panel), and TFP, GDP, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index in both panels. The time period is from 1961:Q1 to 2010:Q4. The dashed red lines represent +/- one standard deviation confidence bands obtained by drawing from the posterior.

Table C1 Distribution of the Forecast Error Variance

horizon	*Manufacturing Patent-Based News*											
	Output			Consumption			Investment			Hours Worked		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.4	1.8	4.2	0.7	2.3	5.0	0.1	1.0	3.2	0.7	2.4	5.2
4	1.4	4.2	8.7	0.7	2.4	6.1	3.4	7.4	13.0	1.3	4.0	8.2
8	1.1	3.8	8.9	0.6	1.9	5.5	3.3	8.1	14.6	1.0	2.7	7.1
16	1.3	4.4	11.4	0.6	2.3	7.6	4.1	10.9	20.6	1.0	2.8	8.2
20	1.5	4.9	12.9	0.6	2.6	8.5	4.8	12.4	23.2	1.1	3.4	9.6

horizon	*Electronic/Electrical Patent-Based News*											
	Output			Consumption			Investment			Hours Worked		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	1.3	3.6	6.5	3.4	6.3	10.3	0.2	1.4	3.6	4.2	7.4	11.7
4	6.9	12.2	18.5	4.8	9.5	15.4	9.0	14.9	21.8	8.2	13.4	19.7
8	6.9	13.2	21.5	3.7	8.9	16.1	10.3	18.2	27.0	6.1	11.5	19.1
16	8.6	16.6	28.9	3.3	10.5	21.0	14.5	25.2	37.3	4.8	11.0	20.7
20	8.7	18.1	31.7	3.1	11.0	23.7	16.7	28.0	41.2	4.9	11.9	23.3

horizon	*Business Services Patent-Based News*											
	Output			Consumption			Investment			Hours Worked		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.9	2.8	5.7	1.9	4.1	7.4	0.1	0.8	2.7	0.0	0.4	1.8
4	2.5	6.1	11.1	2.3	5.3	10.2	2.2	5.6	10.6	0.4	1.6	4.5
8	2.1	5.8	11.5	1.5	4.2	9.4	2.4	6.9	13.2	0.5	1.5	4.4
16	1.8	5.2	11.9	1.0	3.3	8.6	2.8	8.2	16.5	0.6	1.7	5.5
20	1.8	5.1	11.8	1.0	3.2	8.6	3.0	8.7	17.6	0.7	2.0	6.4

Note: The table reports distribution of forecast error variance of output, consumption, investment, and hours worked explained by the manufacturing patent-based news shock (top panel) , by the electronic/electrical patent-based news shocks (middle panel) and by the business services patent-based news shocks (bottom panel) at different horizons – namely at 0, 4, 8, 16, and 20 quarters.