Patent-Based News Shocks*

Danilo Cascaldi-Garcia† Marija Vukotić‡

Federal Reserve Board University of Warwick

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Abstract

We exploit firm-level data on patent grants and subsequent reactions of 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 induce a strong permanent effect after five years. These shocks produce 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

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†Federal Reserve Board, International Finance Division, Washington, D.C. 20551, USA; Email address: danilo.cascaldi-garcia@frb.gov

‡University of Warwick, Economics Department, Coventry CV4 7AL, United Kingdom; Email address: M.Vukotic@warwick.ac.uk

and data processing services, within the services sector, play crucial roles in driving our results.

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JEL Classification Codes: E3, E32, L60

1 Introduction

Economists have struggled to understand the relationship between technological improvements and economic cycles throughout history. However, it was not until the seminal work of Beaudry and Portier (2006) revived the idea of expectation-driven business cycles in Pigou (1927) that the literature began to focus more greatly on understanding the role that advance information about technological improvements plays in explaining these cycles.[1] The literature commonly refers to this advance information as technological news shocks. Isolating these 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 relies almost exclusively on exploiting the movements in the utilization-adjusted total factor productivity (TFP) constructed by Fernald (2012) to identify technological news shocks. The most commonly used identifications define technological news shock as the shock that does not affect TFP in the short run but drives most of its variations over some longer horizons.[2] In part because this is an *indirect* measure of technology, these identifications must rely on assumptions that the TFP follows an exogenous process and that, consequently, long-run movements in TFP are solely

[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), Görtz and Tsoukalas (2017), and Cascaldi-Garcia and Galvao (2020).

[2] Both Barsky and Sims (2011) and approaches that follow Francis, Owyang, Roush, and DiCecio (2014) impose zero restriction on the impact response of TFP. However, the former identifies technological news shock as a shock that explains most of the forecast error variance of TFP over a 40-quarter horizon, while the later identifies it as a shock that maximizes forecast error variance of TFP at a 40-quarter horizon. More recently, Kurmann and Sims (2020) propose using the approach of Francis et al. (2014) without the zero-impact restriction.

due to productivity shocks. The literature has recognized that these are strong assumptions for at least three reasons. First, 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 re-allocative shocks), would be confounded with true news shocks when using identifications that maximize the explained variance of TFP, thus misrepresenting the importance of technological news shocks in driving the business cycle. Second, Cascaldi-Garcia (2017) and Kurmann and Sims (2020) show that TFP-based identification schemes are sensitive even to small updates in the TFP series, such as the one recently proposed by Fernald. Third, Bouakez and Kemoe (2017) show that measurement errors in TFP can impair the validity of identifications based on maximizing the explained variance of TFP.

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 micro-level 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 a patent-based innovation index because it combines firm-level data on patent grants with their subsequent stock price movements. These stock price movements represent the reaction 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 it allows us to propose a robust identification scheme that can incorporate TFP into the analysis but does not depend on exploiting TFP movements for news shock identification. Specifically, because 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—we can use a Cholesky recursive formulation, with the patent-based innovation index ordered first in our vector autoregression (VAR). In this setting, errors from the first equation represent the *patent-based news shock*.

Using annual data, KPSS show that a shock to the patent-based innovation index induces a delayed response of TFP and output. Our paper links these important results to the technological news literature.[3] Specifically, our paper offers answers by exploring movements in the quarterly patent-based innovation index and its dynamic relationship with various macroeconomic variables at business-cycle frequencies. Our contribution becomes particularly relevant given concerns expressed in the literature and outlined above regarding the robustness of general findings to different identification assumptions and TFP measurement.

The news shocks identified with our approach are close to true technological improvements for at least two reasons. First, we use data on patents as direct indicators of technological potentials together with movements in market responses during a narrow window of time around patent grant announcements. Therefore, surprise movements in the patent-based innovation index are likely to measure market expectations solely about future technological improvements reflected by patents and not movements potentially related to optimism or animal spirits.[4]

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

[3]The focus of their paper is to uncover reallocation dynamics across firms following an innovation boost. Nevertheless, the authors also provide a simple aggregate analysis. In particular, for each horizon over 5 years, they regress aggregate output (TFP) on its own lags and the patent-based innovation index and report the responses to a unit standard deviation shock in the innovation index over this 5-year horizon. They show that the effect is persistent and significant.

[4]The use of simple patent counts is often criticized in the literature because it does not account for drastic differences in technical and economic significance across patents, potentially miscalculating 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, it is given in terms of dollars and, therefore, is comparable across time and industries.

We show that the response of TFP to the patent-based news shocks closely resembles the predicted path of *diffusion news* described by Portier (2015), 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.

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 effect on impact 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. 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 —that requires various additional features, such as exogenous real wage rigidity or monetary policy that reacts to output growth rather than output gap, to make TFP-based empirical news literature findings consistent with a New Keynesian model (see, for example, Barsky and Sims, 2009, Jinnai, 2013 and Di Casola and Sichlimiris, 2018). Our results show that all these additional features are not needed. Moreover, Bouakez and Kemoe (2017) argue 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. Because our identification does not rely on any assumptions regarding TFP, it reinforces the claim that the patent-based news shocks we identify represent "true" technological news shocks.

The patent-based news shock explains essentially zero short-run variations in TFP and about 17 percent of variations at a five-year horizon, suggesting that it carries relevant information about future productivity movements in line with the idea behind a technological news shock. At the same time, this shock explains only a small part of the forecast error variance of main macroeconomic aggregates, and less than typically found in the empirical literature on news shocks. When interpreting these results, one should keep in mind that we might be underestimating the importance of news shocks for three reasons. First, not all innovative activity is patented. Second, the patent-based innovation index only considers publicly listed companies. Third, the patent-based index captures direct positive effects of patents, but does not measure positive knowledge spillover effects and potential negative effects from business stealing from competitors. Bloom et al. (2013) investigate externalities induced by R&D spending and show that positive spillover effects more than compensate these negative effects. Nonetheless, the contrast between high explanation power of movements in TFP and low explanation power of movements in real economic variables suggests that technological news shocks cannot be the main driver of business-cycle fluctuations.

We also provide industry evidence demonstrating 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, an identified patent-based news shock that exclusively considers these industries produces a perfect zero effect on impact, before slowly growing to a new higher level. Furthermore, it accounts for 25 percent of TFP variations after five years. In another important industry, Business services, a patent-based news shock produces a significant positive effect 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. The industry evidence lends further support to our approach capturing expectations about future technological improvements.

We show that our main results are robust to using the patent-based innovation index as an instrument for innovative activity in a Bayesian proxy SVAR setting following the methodology of Caldara and Herbst (2019), that builds up from 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, was initiated by Cascaldi-Garcia (2018), who employs forecast revisions from professional forecasters as exogenous instruments.

This paper links to the work of Shea (1999) and Christiansen (2008), who exploit patent data to identify surprise technology shocks. Our paper also relates to the work of Baron and Schmidt (2014), who use technology standardization to identify technological shocks that diffuse slowly into the economy. Finally, our paper is complementary to Miranda-Agrippino et al. (2019), which was the first paper to relate patents to technological news shocks. Specifically, the authors propose a proxy for technological news shocks based on the number of patents registered with the U.S. Patent and Trademark Office (USPTO). We add to their work by exploiting stock market valuations of patents to estimate the real (expected) economic effects of these innovations.

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 briefly describes the data and the identification procedure. Section 4 presents the main results. Section 5 discusses the relationship 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 using a Bayesian proxy SVAR with the patent-based innovation index as an instrument. 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. To this end, we provide some illustrative examples of patents in the Appendix A and explain why we believe they are directly related to the notion of technological news shocks.

We identify technological news shocks using a measure, proposed by KPSS, that combines micro-level data on patents 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 micro-level data to learn about relevant aggregate shocks. 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. 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." Furthermore, he also argues that 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 in this approach is the large volatility of stock market data, and as a result, "the needle might be there but the haystack can be very large." We argue that specific stock market variations exploited by KPSS can be used to beneficial effect in this context. This approach can improve the odds of finding the proverbial needle in the haystack, and can enhance the ability to identify technological news shocks.

2.1 KPSS Innovation Index

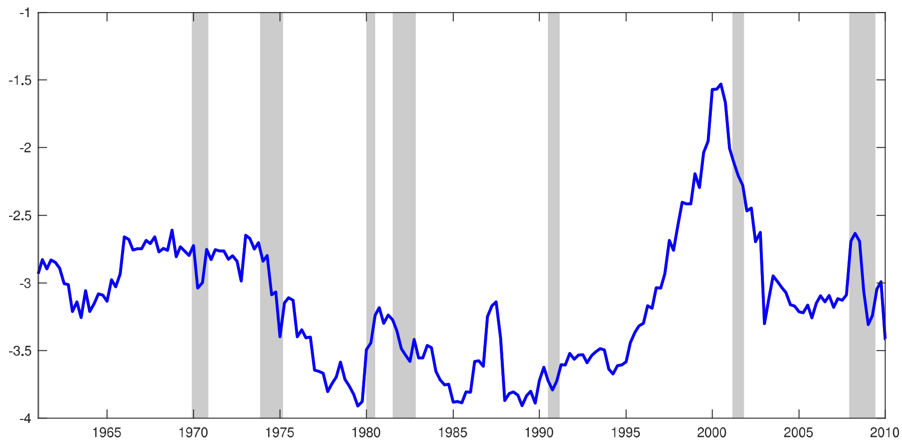
The KPSS aggregate innovation index is constructed by using rich firm-level datasets. They estimate the economic value of the patent by combining data on patents issued to U.S. firms during the 1926–2010 period with firm stock price movements. In particular, by merging Google Patents with the Centre for Research in Security Prices (CRSP) database, they obtain a database of 1,928,123 patents and subsequent stock price movements. The biggest challenge these authors face is to carefully extract the information about the economic value of 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. These particular days 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 (2019), 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. We study the period after 1961:Q1 to account for data availability on consumer confidence, an essential variable in the news literature. We refer to this measure as the *patent-based innovation index*. The contemporaneous correlation with output over business-cycle frequencies is 0.20, suggesting only a mild procyclicality of the index. Not surprisingly, the volatility of the index is much larger than that of output at business-cycle frequencies (standard deviations of 16.08 versus 1.98, respectively).

The value of the index seems to follow times of speculation in the market and especially 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, consistent with the analysis of Nicholas (2008). There are few high-frequency patenting companies in the sample. For example, 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

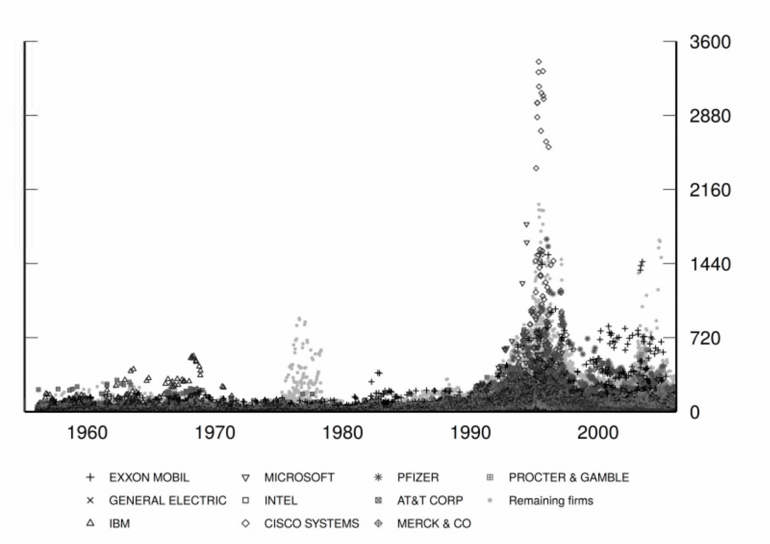
Figure 1 Quarterly Patent-Based Aggregate Innovation Index



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 shaded vertical bars represent the NBER-dated recessions.

value from 1961 to 2010 with all their patent values throughout the sample.

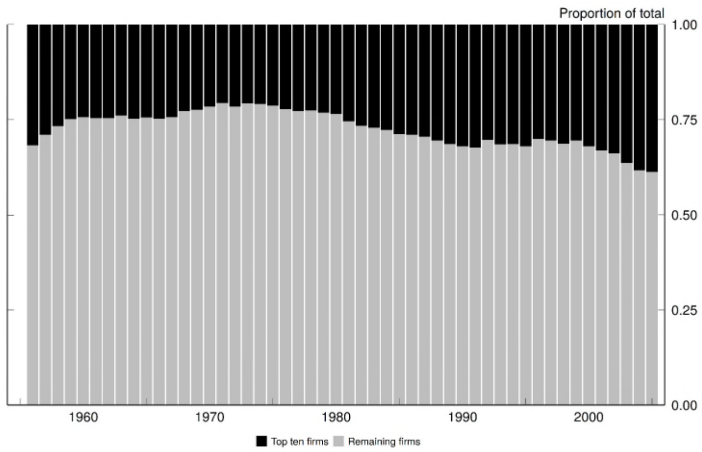
Figure 2 Value of Patents by Company



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

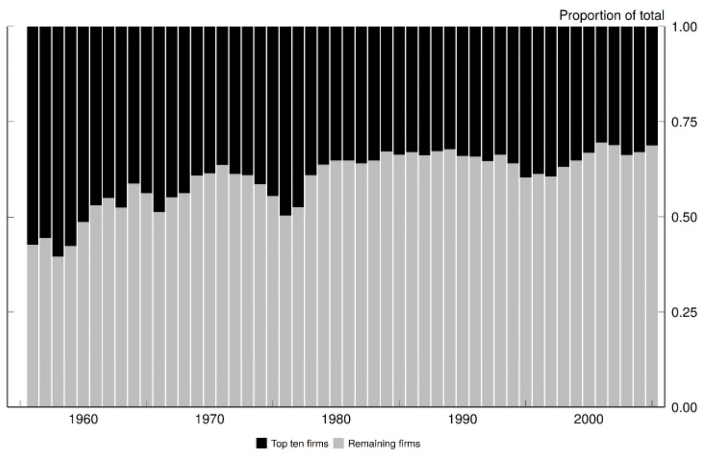
Figures 3 and 4 represent the share of total number (and value) of patents by top 10 firms in each year. The share of these firms, both in terms of number and value of patents, is consistently higher than 25 percent and, in some periods, even as high as 50 percent. The detailed list of top ten firms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

Figure 3 Share of total number of patents by top ten firms 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 Share of total value of patents by top ten firms per year



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

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. Such criticisms pertain to the issue of drastic differences in technical and economic significance 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.[5]

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). By narrowing the forward-looking component to the specific market responses to announcements of patent grants, the patent-based measure is likely to capture market expectations based on future economic fundamentals, not on optimism, confidence, and animal spirits.

Fourth, using micro-level data on patents and their stock market evaluations allows us to propose an alternative, direct way to identify news shocks, independent of movements in TFP. Nevertheless, we include TFP in our analysis and show that it moves as expected, clearly validating our analysis by establishing a direct link with the existing literature on the news shocks.

Overall, rather than focusing on proposing a novel statistical procedure that would recover news shocks by exploiting fluctuations in TFP, we approach this problem differently by using micro-level 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.

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

[5]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.

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.

3 Data, Bayesian VAR, and Identification Procedure

The information set contains a combination of technology, real macroeconomic, and forward-looking variables. We estimate our benchmark VAR model with 10 endogenous variables, namely patent-based innovation index, utilization-adjusted TFP (Fernald, 2012), output, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index. We relegate the details of the series other than the patent-based innovation index, much more commonly used in the literature, to the Online Appendix. 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. 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). Coverage bands for the impulse response graphs are computed using 1,000 draws from the posterior distribution.

The patent-based news shock is identified under a conventional lower triangular Cholesky decomposition, where the patent-based innovation index is ordered first in the information set. The use of a VAR is appropriate in this context because it purges the patent-based technology index from any lagged predictability. In fact, none of the endogenous variables predict the filtered patent-based technology index, i.e., patent-based news shock. First, none of the endogenous variables Granger cause patent-based news shocks.[6] Second, the correlations between our patent-based news shock and other structural shocks in the literature —news about tax shocks, oil price shocks, monetary policy shocks, and

[6]The F-values of the Granger causality test are all lower than the 5 percent critical value and amount to 0.83, 0.29, 0.59. 0.53, 1.25, 0.25 and 2.78 for TFP, investment, consumption, output, hours, stock prices and consumer confidence, respectively.

tax shocks —are rather small and insignificant. The correlations (and p-values) are 0.12 (0.37), -0.06 (0.46), 0.08 (0.39), -0.10 (0.37), respectively. The shock is mildly positively correlated with news about government spending shock (0.20), but it is not statistically significant at a 5 percent level. This mild correlation might reflect a positive response of government spending to the exogenous technological improvements.

We opt to present our results as impulse responses from the VAR as a benchmark. Plagborg-Møller and Wolf (2019) argue that linear local projections (Jorda, 2005) and VARs estimate the same impulse responses in population. Moreover, when only a finite p number of lags of data are included in the VAR and in the local projection, these methods only agree up to p horizons ahead. However, Kilian and Kim (2011)'s simulations show that the coverage accuracy of confidence intervals from local projections are less accurate than the equivalent VAR, especially in small samples. Since this paper deals with data in quarterly frequency, which limits the size of the sample, and we are also interested in the medium- and long-run effects of the shock (up to 20 quarters ahead, and not only up to the p-included lags), we opted for the VAR approach. Notwithstanding, we do perform local projections of the patent-based news shock as a robustness check, briefly described in the following section and documented in the Online Appendix.

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 real macroeconomic and forward-looking variables. 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 responses of the patent-based innovation index and TFP to a patent-based news shock. As expected, the innovation index increases on impact with the shock, explaining 100 percent of its variations by construction. The shock remains quite persistent, explaining 84 percent of index variations after 4 quarters, 64 percent after 8 quarters, 41 percent after 16 quarters and, finally, 37 percent after 20 quarters.

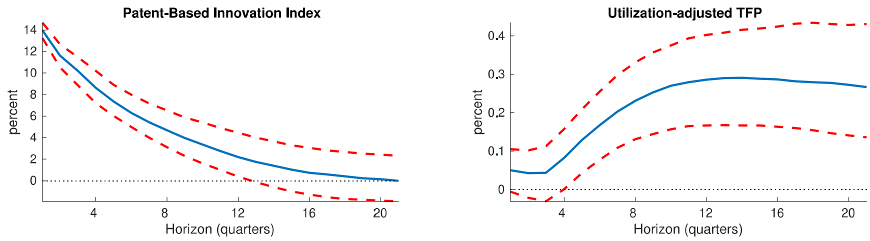
Even though the impact response of TFP is *not* restricted, the coverage bands do not rule out a zero effect.[7] After a slightly small and insignificant initial jump, TFP decreases for about a year before slowly picking up and converging to its new long-run level. This slight decrease of aggregate TFP before it starts to rise might be a reflection of a creative destruction that is also documented by KPSS at the firm level. 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. 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.[8]

[7] It is important to emphasize that this result is not easily achieved without restricting the impact response of TFP to zero. In fact, when the same time period and data (except patent-based innovation index) as in our benchmark specification is used, TFP's impact response to TFP-based news shocks when zero restriction is not imposed is about 0.7 percent when using Barsky and Sims, 2011, and 0.2 percent when using Francis et al., 2014. We document these results in the Online Appendix.

[8] 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.

Figure 5 Responses of Patent-Based Innovation Index and 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, output, 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 TFP response presented in Figure 5 also resembles a process that follows a slow diffusion of new innovative activity, as discussed by Portier (2015). This response is in line with the specific 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.

The attractive feature of our identification is that it does not rely on imposing any assumptions about short- and long-run behavior of TFP and that 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. We also adopt this as our benchmark case. However, as Figure B1 in the Appendix illustrates, the responses to a patent-based news shock are almost identical regardless of whether productivity is adjusted for capacity utilization.

Finally, as an additional check, we perform a local projection of the patent-based news shock on utilization-adjusted TFP, following methodology proposed by Jorda, 2005. As presented in the Online Appendix (Figure C.1), 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 additional evidence of the power of the patent-based news shock in capturing the technological diffusion characterized by the news shock literature.[9]

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.

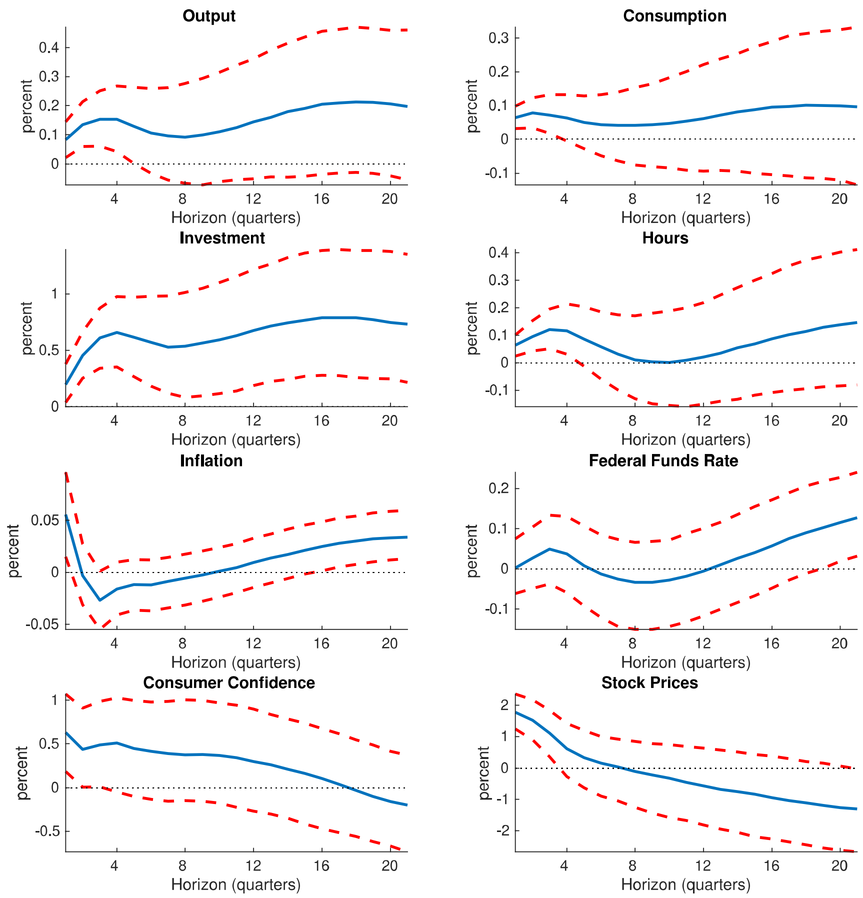
A patent-based news shock induces a clear comovement among output, consumption, investment, and hours. Output increases by about 0.1 percent on impact. Interestingly, much of this increase is dictated by investment behavior. In particular, the 0.2 percent impact response of investment is higher than 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 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 five 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 effect on impact 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. While inflation rises mildly on impact, the response of the federal funds rate does not rule out a zero effect. The positive response of the federal funds rate in the short run is in line with the initial increase in inflation and with the predictions of a standard New Keynesian model. This result is not easily achieved in the news literature (see, for example, Barsky and Sims, 2011; Kurmann and Sims, 2020; Barsky et al., 2015).

[9]Local projections of the patent-based news shock on other macroeconomic variables are qualitatively similar to the ones presented in Figure 6. Figure C.2 in the Online Appendix documents these results.

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, utilization-adjusted TFP, output, 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.

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 in contrast to 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 explains part of future TFP movements. Furthermore, this result does not come as a surprise given our previous

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	0.1	0.5	2.0	0.1	0.9	2.8	0.4	1.7	3.9	0.1	0.7	2.7
4	0.5	1.7	4.6	0.5	2.0	5.2	0.4	1.4	4.1	1.3	4.0	8.3
8	2.2	6.9	13.3	0.5	1.8	5.4	0.4	1.3	3.7	1.2	4.3	9.7
16	5.7	15.1	25.2	0.8	2.6	7.9	0.5	1.9	5.7	2.0	6.7	14.8
20	6.3	16.5	26.8	0.9	3.1	9.1	0.5	2.1	6.7	2.3	7.7	16.7

horizon	Hours Worked			Inflation			Consumer Confidence			Stock Prices		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.2	1.4	3.6	0.1	1.0	2.9	0.2	1.2	3.3	2.9	5.8	9.7
4	0.5	1.6	4.3	0.7	1.8	3.5	0.4	1.5	4.3	1.6	3.1	6.6
8	0.5	1.4	3.7	0.8	2.1	4.1	0.6	1.9	5.7	1.5	2.9	5.8
16	0.6	1.7	5.7	1.4	3.0	5.3	0.9	2.8	7.1	1.6	3.6	8.1
20	0.7	2.3	7.1	1.9	3.8	6.9	1.1	3.3	7.3	1.8	4.3	9.9

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.

assertion regarding the patent-based index Granger causing TFP and the patent-based index being significantly correlated with TFP only after about 20 quarters.

Second, the patent-based news shock explains about 8 percent of the variation in investment in the long run. Interestingly, the identified shock explains variations in 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 slightly more of the variations in stock prices on impact than after 20 quarters. 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 about 2 to 4 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. It also induces comovement among output, consumption, investment, and hours, but the low explanation power of movements in these variables suggests that this shock cannot be the main driver of business-cycle fluctuations. 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 put these results into perspective. 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 output variance 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 our identification does not aim at maximizing the forecast error variance of TFP. Moreover, our results are also 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. Patenting itself is a strategic decision, so not all innovations are patented. In addition, this measure captures direct positive effects of patents but does not measure positive knowledge spillover effects and potential negative effects from business stealing from competitors. Bloom et al. (2013) investigate externalities induced by R&D spending and show that positive spillover effects more than compensate these negative effects. Therefore, taking all the channels into consideration, 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.

Finally, when interpreting our results, one could worry that patents surge in response to favorable credit conditions and that, therefore, we are identifying credit supply shocks and not news shocks about future productivity prospects. To address this concern, we first investigate the relationship between the patent-based innovation index and excess bond premium (EBP), a widely-used indicator of credit supply conditions proposed by Gilchrist and Zakrajšek (2012) (GZ henceforth). The two series are displayed in Figure B2. The correlation between the two series is 0.17, indicating that there is no strong comovement. Furthermore, to directly control for credit supply conditions, we include EBP into our benchmark VAR. The responses of our benchmark VAR and a VAR when we control for credit conditions are documented in Figure B3. Our results are robust to the inclusion of credit supply conditions, as the responses originating from the two VARs lie on top of each other. In addition, the EBP declines in the short run and increases in the medium run. This result is in line with the findings of Görtz et al. (2016). In the Online Appendix, we show that the results are robust also when other two commonly used indicators of credit conditions, namely GZ credit spread and the BAA-AAA corporate spread, are analyzed instead.

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 serve as the wellspring of technological news, 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). This result is in line with Vukotić (2019), who shows that aggregate news shocks propagate mainly through these same industries within the manufacturing sector. These three industries account for 63 percent of the total number (and 64 percent of the total value) of all patents in Manufacturing.[10]

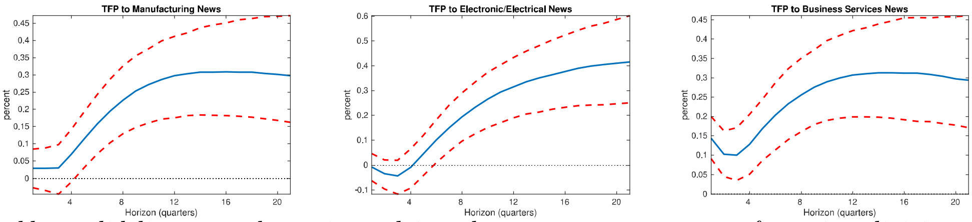
Figure 7 displays the responses of aggregate productivity to a positive shock to the manufacturing patent-based index (left panel) and to the electronic/electrical patent-based news shock (middle panel). In both cases, aggregate TFP does not increase on impact, takes time to become significant, and converges to a new higher value. This pattern is somewhat more pronounced when only patents in electronic/electrical industry are considered. In particular, TFP takes almost two years to become significantly different from zero, then slowly converges 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 the manufacturing sector, and in electronic/electrical industry 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 percent, and the electronic/electrical news shock explains 25 percent of the FEV of TFP after 20 quarters.

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 (17 percent after 20 quarters), consumption (10 percent after 20 quarters), investment (27 percent after 20 quarters), and hours (11 percent 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 *Semicon-*

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

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, output, 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. The industry indices are based on authors' calculations based on Center for Research in Security Prices, CRSP 1925 US Stock Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

ductors and Related Devices; this subindustry accounts for 25 percent of the total number (and 35 percent of the total value) of all patents in electronic/electrical. In addition, it accounts for 70 of the 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 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

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	0.0	0.4	1.4	0.0	0.2	1.1	1.4	3.7	6.7
4	0.4	1.4	3.7	0.4	1.0	2.4	1.5	4.6	8.9
8	2.2	6.4	12.7	2.1	4.8	9.8	4.3	10.3	17.8
16	6.5	16.2	26.8	8.4	19.3	30.7	8.7	19.2	29.7
20	7.7	18.4	29.3	11.7	24.9	37.5	9.4	20.7	32.3

Note: The table reports distribution of forecast error variance of utilization-adjusted 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.

TFP is Services, with Business Services representing 93 percent 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 4 percent of short-run movements in TFP and about 21 percent after 20 quarters.

The reason why TFP jumps on impact most likely relates 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 percent of the total number of patents in business services. The companies that lead the way in this subindustry are Microsoft, accounting for 32 percent, and Oracle, accounting for 11 percent of the total value of patents. Therefore, it is highly likely that most patents that are closely related to programming and data processing are 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 not significant, positive effect on TFP on impact, as shown in Figure 5.

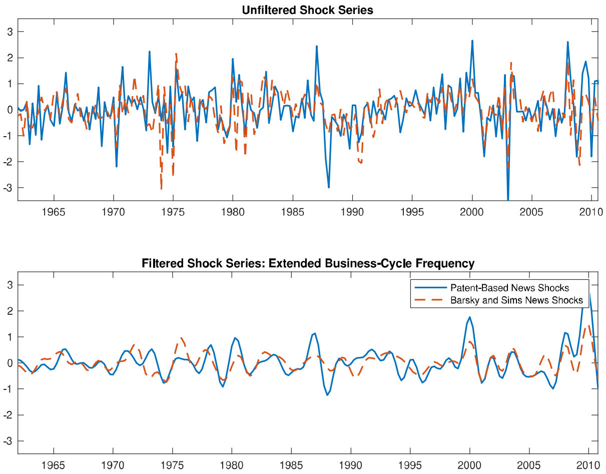
5 Discussion

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, necessary 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).

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



Note: The top panel displays unfiltered series of patent-based news shocks (solid blue line) and news shocks arising from the identification proposed by Barsky and Sims (2011) (dashed red line). 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.

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, to account for the horizon used in the TFP-based identification); this decomposition helps us to understand the degree of comovement between the two series at different horizons. 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 0.69. This result is quite encouraging, considering that our identification strategy does not rely on maximizing the FEV of TFP at any horizon; yet, it is exactly at business-cycle lower frequencies that our shock is more correlated with the TFP-based news shock that, by definition, focuses both on high and low frequencies.

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	0.57
Extended Business-Cycle Frequency, 6-40 quarters	0.69

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.

These results further confirm that our procedure picks up shocks that are closely related to future improvements in technology.

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.

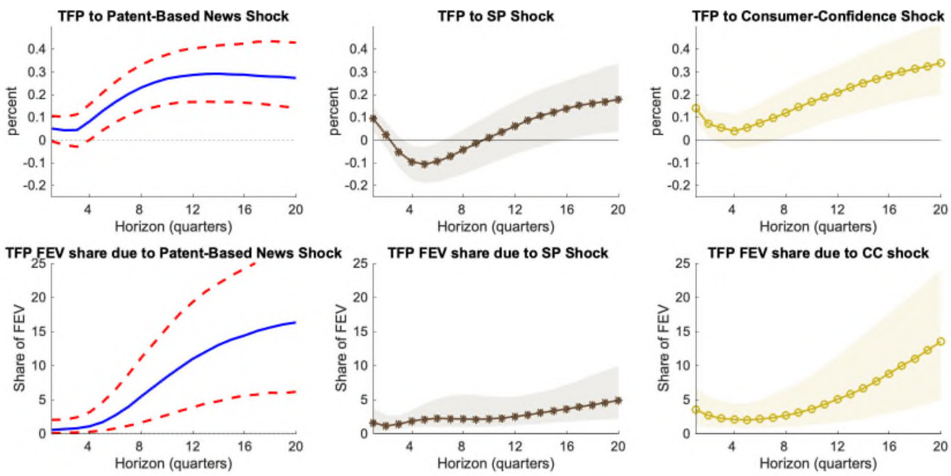
Considering these results, we compare responses to our patent-based news shock with surprise shocks to two aggregate forward-looking variables: stock prices and consumer confidence.[11] We refer to these two shocks as stock price shock and consumer confidence shock, respectively.

[11] 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 surprise shock to the stock price (consumer confidence).

Both the 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.[12] 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 in reference to these three shocks.

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 the utilization-adjusted 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.

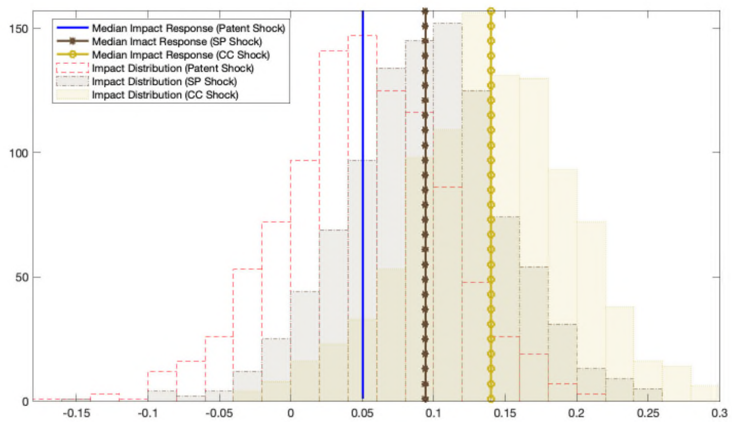
[12] This literature usually views these autonomous fluctuations as having a causal effect on economic activity and the business cycle. See, for example, Barsky and Sims (2012), Angeletos and La'O (2013), Benhabib et al. (2015), Angeletos et al. (2018) and Levchenko and Pandalai-Nayar (2020).

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 rises 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 the patent-based news shock 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, suggests that the information contained in the patent-based index is an important force behind the TFP diffusion.

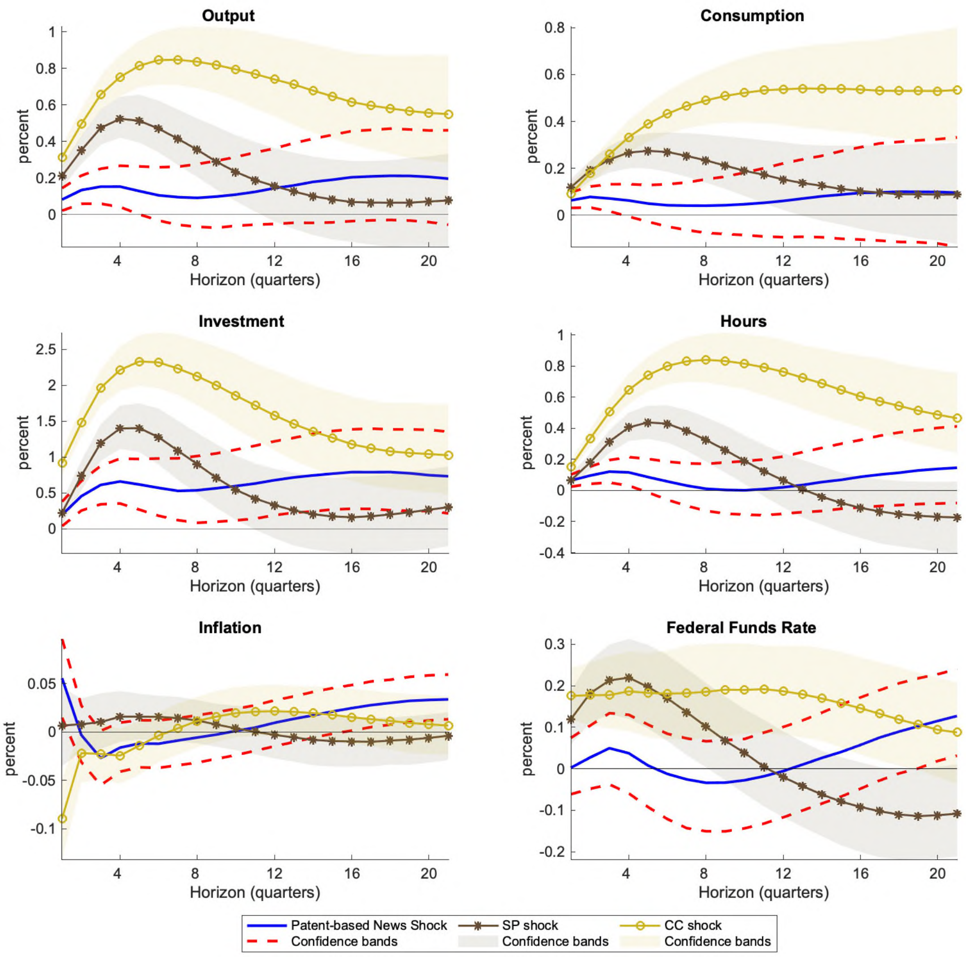
Figure 10 Distribution of TFP Impact Response to Patent-Based News, Stock Price and Consumer Confidence Shocks



Note: Distribution and median of TFP impact response to a patent-based news shock, stock price shock, and consumer confidence shock. Histograms constructed over all 1,000 posterior draws. The time period is from 1961:Q1 to 2010:Q4.

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.

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



Note: The figure displays baseline 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 to 2010:Q4.

We believe that these results are supportive of our previous assertion. First, larger responses 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 both a much smaller part of TFP variations and larger variations of these macroeconomic variables than is the case with a patent-based news shock. This observation is quite telling. If the shock is truly about future variations in productivity, then one would expect for this shock to explain at least as much, if not more, of TFP variations 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-cycle literature to identify several types of structural shocks.[13] For technological news shocks, Cascaldi-Garcia (2018) employs a constructed series of forecast revisions from

[13]Some examples are monetary policy shocks (Stock and Watson, 2012; Gertler and Karadi, 2015; Miranda-Agrippino and Ricco, 2020; 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., 2020), news about future fiscal spending (Auerbach and Gorodnichenko, 2012), and news about future oil supply (Arezki et al., 2017).

the Federal Reserve Bank of Philadelphia Survey of Professional Forecasters (SPF) about future GDP, investment, and industrial production as instruments. Miranda-Agrippino et al. (2019) instrument the structural news shock through the unforecastable component of the number of granted patents filed at the 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 relationship 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[14] 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.

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 percent 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.[15]

We estimate and identify the patent-based news shock through the Bayesian Proxy SVAR method proposed by Caldara and Herbst (2019). The method benefits of incorporating all sources of uncertainty both on the reduced-form and structural parameters identified by the proxy. We estimate the reduced-form using a standard Minnesota priors

[14] 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.

[15] 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 percent level), and of 0.17 with news about government spending (statistically significant at a 10 percent 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]

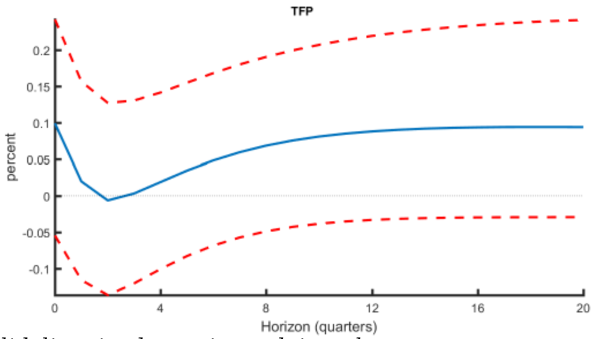
Note: Values in brackets are p-values for the test of zero correlation under the null hypothesis and are computed by taking into account the false discovery rate of positively dependent tests, following the methodology by Benjamini and Hochberg (1995). Correlations range from 1969:Q1 to 2006:Q4 due to data availability.

structure (Litterman, 1986) similar to the Bayesian VAR in Section 3. We employ the high relevance prior for the standard deviation of the measurement error, which determines the tightness of the relationship between the proxy and the SVAR model. The results are also robust to employing the inverse Gamma prior.

The information set is the same as described in Section 3, with the exception that now it 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 presented in Figure 5 identified with our benchmark model.

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



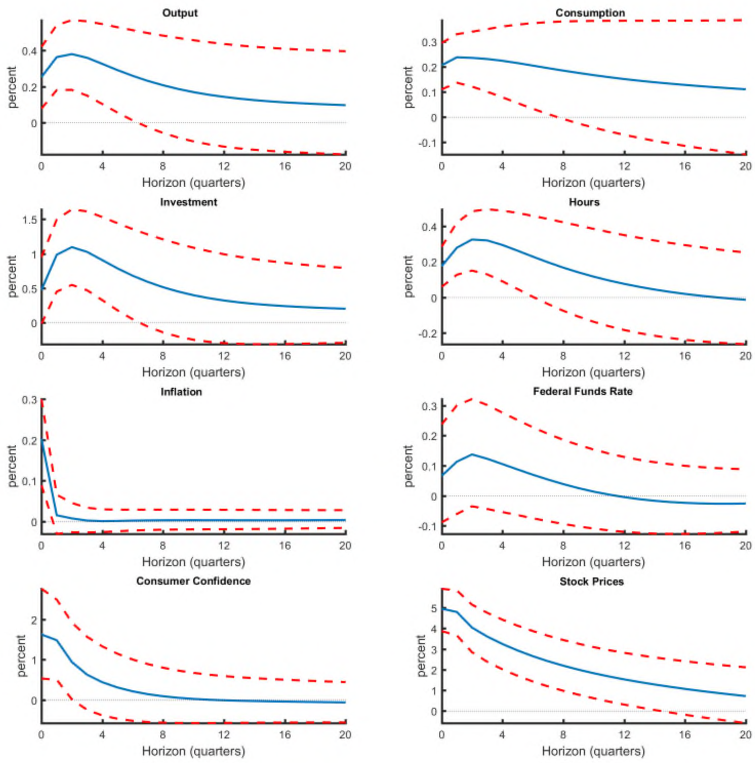
Note: The blue solid line is the estimated impulse response to a patent-based news shock identified under a Bayesian Proxy SVAR (Caldara and Herbst, 2019) with the patent-based innovation index as an instrument and corresponds to the posterior median estimate. The unit of the vertical axis is the percentage deviation from the situation without a shock. The response originates from a VAR composed of TFP, output, 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.

7 Conclusion

This paper contributes to the news literature by exploiting sound micro-level data directly related to technological innovations rather than relying on movements in a 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 innovation to 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 induce a strong permanent effect in TFP after five years and do not affect it 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

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 Bayesian Proxy SVAR (Caldara and Herbst, 2019) 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, output, 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.

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 their 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.

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 crucial roles in driving our results.

Identifying technological news shocks is a difficult task due to the complex process of estimating the aggregate technology level. Exploring micro-level 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 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.

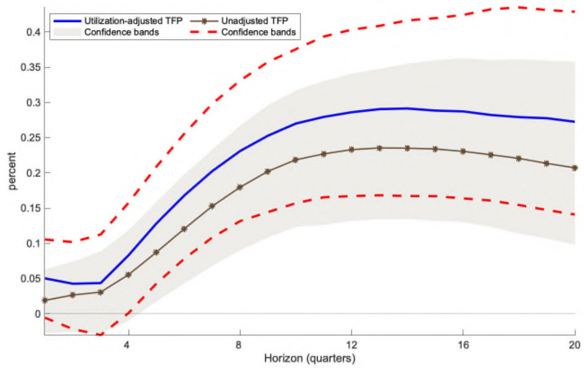
Another example that illustrates the importance of the dissemination of the information released with a patent grant is patent 4,131,919, awarded to Eastman Kodak Company on December 26, 1978, for the invention of the “electronic still camera that employs a nonvolatile reusable storage medium for recording scene images”– the first self-contained digital camera. Although Kodak did not 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. In particular, 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 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.

Appendix B Robustness

B.1 Utilization-adjusted and unadjusted TFP

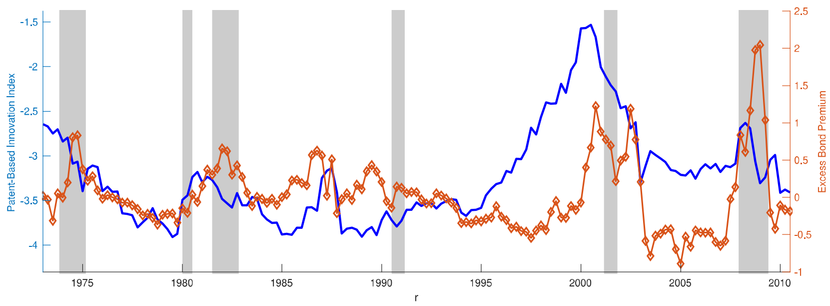
Figure B1 Responses of (Un)adjusted TFP to a Patent-Based News Shock



Note: The figure 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 responses originate from a VAR composed of the patent-based innovation index, TFP (adjusted or unadjusted), output, 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.

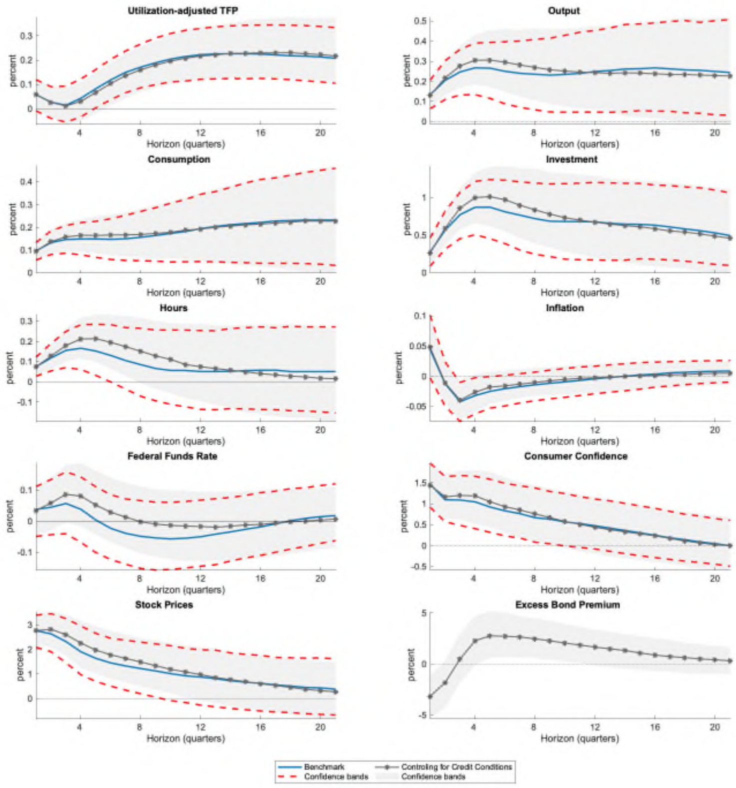
B.2 Controlling for Credit Market Conditions

Figure B2 Patent-Based Innovation Index and Excess Bond Premium



Note: Log of the aggregate patent-based quarterly index (solid blue line) and the Excess Bond Premium as calculated by Gilchrist and Zakrajšek (2012) (red diamond line), spanning 1973:Q1 - 2010:Q4. The shaded vertical bars represent the NBER-dated recessions.

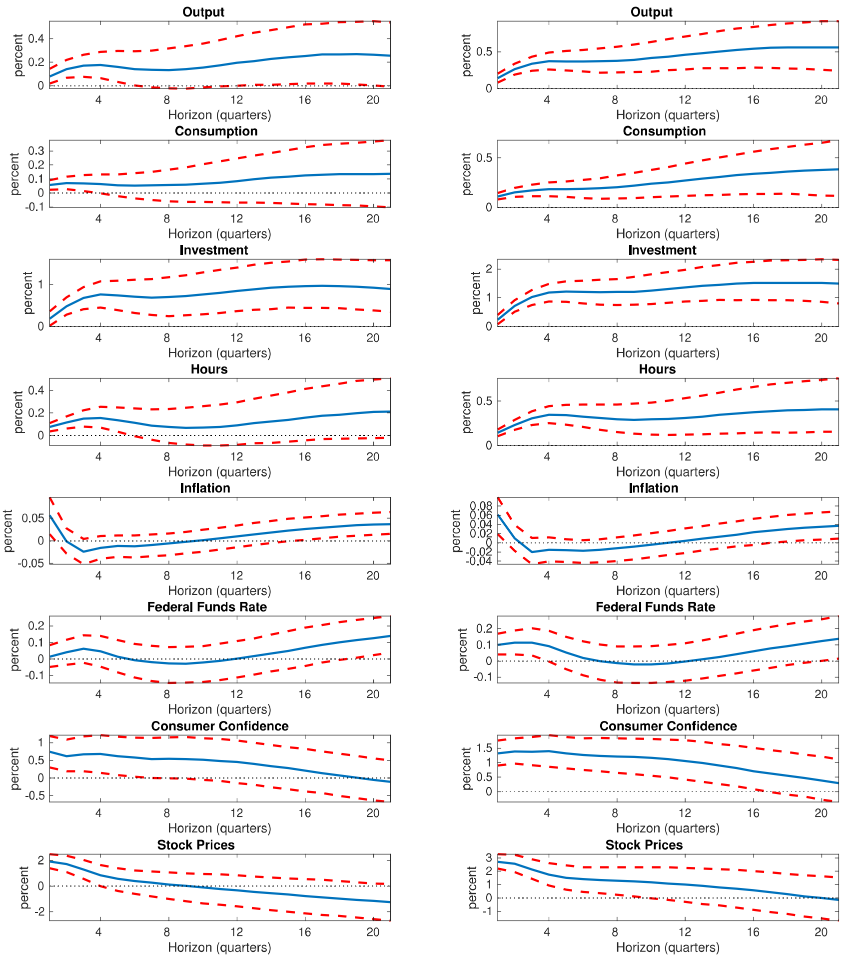
Figure B3 Responses to Patent-Based News Shocks: Benchmark vs When Controlling for Credit Conditions



Note: The figure compares benchmark responses with those when we control for credit conditions. The benchmark responses originate from a VAR composed of the patent-based innovation index, utilization-adjusted TFP, output, consumption, investment, hours, inflation, the federal funds rate, consumer confidence, and the stock price index, while in the case when we control for credit conditions in addition to all these variables EBP is added. The time period is from 1973:Q1 - 2010:Q4. Shaded areas and dashed red lines represent +/- one standard deviation confidence bands obtained by drawing from the posterior.

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 panel) 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 utilization-adjusted TFP, output, 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. The indices are based on authors' calculations based on Center for Research in Security Prices, CRSP 1925 US Stock Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

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	0.1	0.9	2.7	0.3	1.3	3.4	0.1	0.6	2.5	0.5	1.9	4.3
4	0.6	2.4	5.8	0.4	1.3	3.8	1.9	5.2	9.9	0.8	2.5	5.9
8	0.6	2.3	6.6	0.4	1.3	3.9	2.0	6.0	12.1	0.7	1.8	5.1
16	0.9	3.5	9.9	0.5	1.9	6.5	3.3	9.5	19.1	0.7	2.4	7.4
20	1.1	4.2	11.7	0.5	2.2	7.9	3.9	11.1	21.6	0.9	3.0	9.3

horizon	*Electronic/Electrical Patent-Based News*											
	Output			Consumption			Investment			Hours Worked		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.9	2.6	5.4	2.8	5.2	8.5	0.2	1.1	3.0	3.9	7.2	11.1
4	5.3	9.8	15.9	3.4	7.6	12.7	7.4	12.7	19.3	7.0	11.6	17.7
8	5.5	11.2	19.3	2.6	7.4	14.0	8.5	15.9	24.6	5.0	9.9	17.2
16	7.2	15.4	27.3	2.6	9.2	19.7	13.6	23.6	36.4	4.3	10.2	19.9
20	7.9	17.1	30.0	2.7	9.9	22.3	15.6	26.8	39.9	4.5	11.4	23.1

horizon	*Business Services Patent-Based News*											
	Output			Consumption			Investment			Hours Worked		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	0.7	2.3	4.9	1.7	3.8	6.8	0.1	0.7	2.5	0.1	0.5	1.9
4	2.1	5.2	9.6	1.8	4.5	9.1	1.8	5.0	9.7	0.4	1.5	4.5
8	1.7	5.2	10.5	1.2	3.7	8.5	2.1	6.1	12.5	0.4	1.5	4.2
16	1.6	4.8	11.4	0.9	3.0	8.3	2.7	7.9	16.1	0.6	1.7	5.5
20	1.6	4.6	11.1	0.9	2.9	8.2	2.9	8.4	17.5	0.6	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.