Technological Innovation, Resource Allocation and Growth*

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May, 2016

Abstract

We propose a new measure of the economic importance of each innovation. Our measure uses newly collected data on patents issued to US firms in the 1926 to 2010 period, combined with the stock market response to news about patents. Our patent-level estimates of private economic value are positively related to the scientific value of these patents, as measured by the number of citations that the patent receives in the future. Our new measure is associated with substantial growth, reallocation and creative destruction, consistent with the predictions of Schumpeterian growth models. Aggregating our measure suggests that technological innovation accounts for significant medium-run fluctuations in aggregate economic growth and TFP. Our measure contains additional information relative to citation-weighted patent counts; the relation between our measure and firm growth is considerably stronger. Importantly, the degree of creative destruction that is associated with our measure is higher than previous estimates, confirming that it is a useful proxy for the private valuation of patents.

JEL classifications: G14, E32, O3, O4

*We thank Hal Varian for helping us in extracting information on Patents from Google Patents database. We are grateful to Andrew Atkeson, Nick Bloom, Andrea Eisfeldt, Yuriy Gorodnichenko, Roel Griep, Pete Klenow, Danielle Li, Jonathan Parker, Tomasz Piskorski, and Heidi Williams for detailed comments. We also thank numerous other discussants and participants at the AEAs, Boston University, Columbia Business School, Duke/UNC Asset Pricing Conference, FRB Chicago, NBER Asset Pricing, NBER Economic Fluctuations and Growth, NBER Entrepreneurship, NBER Productivity, Minnesota, Northwestern, NYU, and SITE for helpful discussions. We are grateful to Tom Nicholas for sharing his patent citations data. The authors thank the Fama-Miller Center at University of Chicago, the Zell Center and the Jerome Kenney Fund for financial assistance.

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Since Schumpeter, economists have argued that technological innovation is a key driver of economic growth. Models of endogenous growth have rich testable predictions about both aggregate quantities and the cross-section of firms, linking improvements in the technology frontier to resource reallocation and subsequent economic growth. However, the predictions of these models are difficult to test directly, mainly due to the scarcity of directly observable measures of technological innovation. To assess the importance of technological innovation for economic growth, an ideal measure should capture the economic value of new inventions, and be comparable both across industries and across time. This paper aims to fill this gap by constructing a new measure of the economic importance of each innovation.

We propose a new measure of the private, economic value of new innovations that is based on stock market reactions to patent grants. We construct this measure combining a novel dataset of patent grants over the period 1926 to 2010 with stock market data.[1] The advantage of using financial data is that asset prices are forward-looking and hence provide us with an estimate of the private value to the patent holder that is based on ex-ante information. This private value need not coincide with the scientific value of the patent – typically assessed using forward patent citations. For instance, a patent may represent only a minor scientific advance, yet be very effective in restricting competition, and thus generate large private rents. These ex-ante private values are useful in studying firm allocation decisions, estimating the (private) return to R&D spending, and assessing the degree of creative destruction and reallocation that results following waves of technological progress. Further, the fact that our measure of 'quality' is in terms of dollars implies that our estimates are comparable across time and across different industries; in contrast, since patenting propensities could vary, comparing patent counts across industries and time becomes more challenging.

We construct an estimate of the private value of the patent by exploiting movements in stock prices following the days that patents are issued to the firm. We first document that trading activity in the stock of the firm that issued a patent increases after the patent issuance date. Second, we find that returns on patent grant days are more volatile than on days without any patent grant announcement, suggesting that valuable information is released to the market. However, even within a narrow window around grant days, stock prices may move for reasons that are unrelated to patent values. To filter the component of firm return that is related to the value of the patent from noise, we make several distributional assumptions. Several robustness checks suggest that our estimates are not overly sensitive to the particular choice of underlying distributions. The resulting distribution of the estimated patent values is fat-tailed, consistent with past research describing the nature of radical innovations (Harhoff, Scherer, and Vopel, 1997). The characteristics of innovating firms and industries are similar to those discussed in Baumol (2002), Griliches (1990), Scherer (1965)

[1] Several new studies exploit the same source of patent data (Google Patents) as we do in our paper. For instance, see Moser and Voena (2012), Moser, Voena, and Waldinger (2012) and Lampe and Moser (2011). Ours is the first to exploit this data at a large scale and match it to firms with stock price data.

and Scherer (1983) who describe firms that have conducted radical innovation and have been responsible for technical change in the U.S.

To illustrate the usefulness of our measure, we use it to examine three important questions in the literature on innovation and growth. Addressing these issues using existing measures has proved to be a challenge. First, the relation between the private and the scientific value of innovation – as measured by patent citations – has been the subject of considerable debate.[2] We examine the relation between our measure and the number of citations that the patent receives in the future. We find that our patent-level estimates of economic value are strongly positively related to forward citations; this correlation is robust to a number of patent- and firm-level controls. Placebo experiments confirm that this relation is unlikely to be spurious. In terms of economic magnitudes, our results are comparable to Hall et al. (2005); an additional patent citation is associated with an increase of 0.1% to 3.2% in the economic value of a patent.

Second, we use our estimate of the market value of innovation to examine the predictions of models of endogenous growth (e.g. Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004). Since the value of a firm's innovative output is hard to observe, constructing direct empirical tests of these models has proven challenging; existing approaches rely on indirect inference (see, e.g. Garcia-Macia, Hsieh, and Klenow, 2015). A unifying prediction of Schumpeterian models of growth is that firms grow through successful innovation – either through acquiring new products or by improving existing varieties. By contrast, innovation by competing firms has a negative effect – either directly through business stealing, or indirectly through movements in factor prices. The strength of these effects depends on the economic value of the new inventions. Our results using several measures of firm size – the nominal value of output, profits, capital and number of employees – suggest that both channels are important. Firms that experience a one-standard deviation increase in their innovation output experience higher growth of 2.5% to 4.6% over a period of five years. Conversely, firms that fail to innovate in an industry that experiences a one-standard deviation increase in its innovative output experience lower growth of 2.7% to 5.1% over the same horizon. In addition to firm growth, we find similar effects on revenue-based productivity (TFPR). Firms that innovate experience productivity increases, whereas those that fall behind see productivity declines. By revealing a strong relation between innovation, firm growth and the reallocation of resources across firms –

[2]For instance, Hall, Jaffe, and Trajtenberg (2005) and Nicholas (2008) document that firms owning highly cited patents have higher stock market valuations. Harhoff, Narin, Scherer, and Vopel (1999) and Moser, Ohmstedt, and Rhode (2011) provide estimates of a positive relation using smaller samples that contain estimates of economic value. By contrast, Abrams, Akcigit, and Popadak (2013) use a proprietary dataset that includes estimates of patent values based on licensing fees and show that the relation between private values and patent citations is non-monotonic. Our approach allows us to revisit this question at a higher level of granularity than Hall et al. (2005), while using a broader sample than Harhoff et al. (1999), Moser et al. (2011) and Abrams et al. (2013).

capital and labor flow to innovating firms and away from their competitors – these findings support the Schumpeterian view of growth and creative destruction.

Third, we assess the role of technological innovation in accounting for medium-run fluctuations in aggregate economic growth and TFP. A notable challenge facing real business cycle models is the scarcity of evidence linking movements in TFP to clearly identifiable measures of technological change. At the aggregate level, whether technological innovation is socially valuable in endogenous growth models depends on the degree to which it contributes to aggregate productivity – as opposed to simply being a force for reallocation and creative destruction. Our firm-level results, when aggregated using all the firms in our sample, are strongly suggestive of a net positive effect of innovation. However, these effects are confined to the sample of public firms that we study. To study the relation between innovation and growth more broadly at the economy level, we construct an aggregate index of innovation based on our estimated patent values. This index is motivated by a simple growth model, in which, under certain assumptions, firm monopoly profits from innovation are approximately linearly related to aggregate improvements in output and TFP. Our index captures known periods of high technological progress, namely the 1920s, the 1960s and the 1990s (Field, 2003; Alexopoulos and Cohen, 2009, 2011; Alexopoulos, 2011). This innovation index is strongly related to aggregate growth in output and TFP. In particular, a one-standard deviation increase in our index is associated with a 1.6% to 6.5% increase in output and a 0.6% to 3.5% increase in measured TFP over a horizon of five years, depending on the specification.

Our measure speaks to the literature that has spent considerable effort in estimating the value of innovative output. The most popular approach consists of using citation-weighted patent counts (Hall et al., 2005). We find that our innovation measure contains considerable information about firm growth in addition to what is contained in patent citations. In particular, we repeat our firm-level analysis replacing our measure with citation-weighted patent counts – both for the firm and for its competitors. When doing so, we find a comparable – though somewhat weaker – relation between the firm's own innovation output and future growth. However, we find no similar negative link between the firm's future growth and the citation-weighted patenting output of its competitors. We find similar results when we include both our estimated patent values and citation-weighted patent counts in the same specification. These findings are consistent with the view that, relative to the patent's forward citations, our estimated value of a patent is a better estimate of its private economic value.

Our work is related to the literature in macroeconomics that aims to measure technological progress. Broadly, there are three main approaches to identifying technology shocks. The first two approaches measure technology shocks indirectly. One approach is to measure technological change – either at the aggregate or at the firm level – through TFP (see e.g. Olley and Pakes, 1996; Basu, Fernald, and Kimball, 2006). However, since these TFP measures are based on residuals, they could incorporate other forces not directly related to technology, such as resource misallocation (see e.g., Hsieh and Klenow, 2009). In the second approach, researchers have imposed model-based restrictions to identify technology shocks either through VARs or through estimation of structural models (see e.g., Gali, 1999; Smets and Wouters, 2003). The resulting technology series are highly dependent on specific identification assumptions. Our paper falls into the third category, which constructs direct measures of technological innovation using micro data (Shea, 1999; Alexopoulos, 2011).[3]

We are not the first to link firm patenting activity to stock market valuations (see, e.g. Pakes, 1985; Austin, 1993; Hall et al., 2005; Nicholas, 2008). In particular, Pakes (1985) examines the relation between patents and the stock market rate of return in a sample of 120 firms during the 1968–1975 period. His estimates imply that, on average, an unexpected arrival of one patent is associated with an increase in the firm's market value of $810,000. The ultimate objective of these papers is to measure the economic value of patents; in contrast, we use the stock market reaction as a means to an end—to construct appropriate weights for an innovation measure which we can be employed to study different issues in the literature on innovation and growth.

Our paper contributes to the literature that studies the determinants of firm growth rates. Early studies show considerable dispersion in firm growth that is weakly related to size (see, e.g. Simon and Bonini, 1958). Our paper is related to the growing body of work that explores the link between innovation and firm growth dynamics (Caballero and Jaffe, 1993; Klette and Kortum, 2004; Lentz and Mortensen, 2008; Acemoglu, Akcigit, Bloom, and William, 2011; Garcia-Macia et al., 2015). Existing approaches rely on calibration or estimation of structural models. In contrast, our approach consists of building a direct measure of technological innovation implied by our model and using that measure to test the model's predictions directly. Our paper is also related to work that examines whether technological innovation leads to positive knowledge spillovers or business stealing. Related to our paper is the work of Bloom, Schankerman, and Van Reenen (2013), who disentangle the externalities generated by R&D expenditures on firms competing in the product and technology space. We contribute to this literature by proposing a measure of patent quality based on asset prices and assessing reallocation and growth dynamics after bursts of innovative activity.

[3]Shea (1999) constructs direct measures of technology innovation using patents and R&D spending and finds a weak relationship between TFP and technology shocks. Our contrasting results suggest that this weak link is likely the result of the implicit assumption in Shea (1999) that all patents are of equal value. Indeed, Kortum and Lerner (1998) show that there is wide heterogeneity in the economic value of patents. Furthermore, fluctuations in the number of patents granted are often the result of changes in patent regulation, or the quantity of resources available to the US patent office (see e.g. Griliches, 1990; Hall and Ziedonis, 2001). As a result, a larger number of patents does not necessarily imply greater technological innovation. Using R&D spending to measure innovation overcomes some of these issues, but doing so measures innovation indirectly. The link between inputs and output may vary as the efficiency of the research sector varies over time or due to other economic forces (see e.g., Kortum, 1993). The measure proposed by Alexopoulos (2011) based on books published in the field of technology overcomes many of these shortcomings. However, this measure is only available at the aggregate level, and may not directly capture the economic value of innovation to the firm. In contrast, our measure is available at the firm level, which allows us to evaluate reallocation and growth dynamics across firms and sectors.

Finally, our paper is also related to productivity literature that has documented substantial dispersion in measured productivity across plants and firms (see e.g., Syverson, 2004). We contribute to this literature by constructing a direct measure of technological innovation and showing that it can account for a significant fraction of cross-firm dispersion in measured TFP in our sample.

1 Construction of the Innovation Measure

Our main objective in this section is to obtain an empirical estimate of the economic value of the patent, defined as the present value of the monopoly rents associated with that patent. To estimate this value, we combine information from patent data and firm stock price movements. We proceed in two steps.

The first empirical challenge is to isolate the information about the value of the patent contained in stock prices from unrelated news. To do so, we focus on a narrow window following the date when the market learns that the patent application is successful. The US Patent Office (USPTO) has consistently publicized successful patent applications throughout our sample. Focusing on the days around this event allows us to isolate a discrete change in the information set of the market participants regarding a given patent. However, even during a small window around the event, stock prices are likely to be contaminated with other sources of news unrelated to the value of the patent. Therefore, our second step filters the stock price reaction to the patent issuance from the total stock return over the event window. Next, we discuss the data used in constructing our measure and describe these two steps in more detail.

1.1 Description of patent data

We begin by first providing a brief description of the patent data; we relegate the details to the Online Appendix. We download the entire history of U.S. patent documents (7.8 million patents) from Google Patents using an automation script.[4] First, we clean assignee names by comparing each assignee name to the more common names, and if a given name is close, according to the Levenshtein distance, to a much more common name, we substitute the common name for the uncommon name. Having an assignee name for each patent, we match all patents in the Google data to corporations whose returns are in the CRSP database. Some of these patents appear in the NBER data set and therefore are already matched to CRSP firms. Remaining assignee names are matched to CRSP firm names using a name

[4]Google also makes available for downloading bulk patent data files from the USPTO. The bulk data does not have all of the additional "meta" information including classification codes and citation information that Google includes in the individual patent files. Moreover, the quality of the text generated from Optical Character Recognition (OCR) procedures implemented by Google is better in the individual files than in the bulk files provided by the USPTO. This is crucial for identifying patent assignees.

matching algorithm. Visual inspection of the matched names confirms very few mistakes in the matching. We extract patent citations from the Google data and complement them with the hand-collected reference data of Nicholas (2008).[5]

Out of the 6.2 million patents granted in or after 1926, we find the presence of an assignee in 4,374,524 patents. After matching the names of the assignees to public firms in CRSP, we obtain a database of 1,928,123 matched patents. Out of these patents, 523,301 (27%) are not included in the NBER data. Overall, our data provides a matched permco for 44.1% of all patents with an assignee and 31% of all granted patents. By comparison, the NBER patent project provides a match for 32% of all patents from 1976–2006, so our matching technique is comparable, even though we use only data extracted from OCR documents for the period before the NBER data. Last, another point of comparison is Nicholas (2008), who uses hand-collected patent data covering 1910 to 1939. From 1926–1929, he matches 9,707 patents, while our database includes 8,858 patents; from 1930–1939 he has 32,778 patents while our database includes 47,036 matches during this period. After restricting the sample of patents to those with a unique assignee, those issued while the firm has non-missing market capitalization in CRSP, and for which we can compute return volatilities, we obtain a final sample of 1,801,879 patents.

1.2 Identifying information events

The first step in constructing our measure is to isolate the release of information to the market. The US Patent and Trademark Office (USPTO) issues patents on Tuesdays, unless there is a federal holiday. The USPTO's publication, *Official Gazette*, also published every Tuesday, lists patents that are issued that day along with the details of the patent. Identifying additional information events prior to the patent issue day is difficult, since before 2000, patent application filings were not officially publicized (see, e.g., Austin, 1993). However, anecdotal evidence suggests that the market often had advance knowledge of which patent applications were filed, since firms often choose to publicize new products and the associated patent applications themselves. For now, we assume that the market value of the patent, denoted by ξ, is perfectly observable to market participants before the patent is granted. We show how relaxing this assumption affects our measure in Section 1.4 below.

[5]For the Google data, we extract patent citations from two sources. First, all citations for patents granted between 1976 and 2011 are contained in text files available for bulk downloading from Google. These citations are simple to extract and likely to be free of errors, as they are official USPTO data. Second, for patents granted before 1976, we extract citations from the OCR text generated from the patent files. We search the text of each patent for any 6- or 7-digit numbers, which could be patent numbers. We then check if these potential patent numbers are followed closely by the corresponding grant date for that patent; if the correct date appears, then we can be certain that we have identified a patent citation. Since we require the date to appear near any potential patent number, it is unlikely that we would incorrectly record a patent citation – it is far more likely that we would fail to record a citation than record one that isn't there.

On the patent issue date, the market learns that the patent application has been successful. Absent any other news, the firm's stock market reaction ΔV on the day the patent j is granted would be given by

$$\Delta V_j = (1 - \pi_j)\, \xi_j, \tag{1}$$

where, π_j is the market's ex-ante probability assessment that the patent application is successful and ξ_j is the dollar value of patent j. The market's reaction to the patent grant (1) understates the total impact of the patent on the firm value, since the information about the probability that a patent will be granted is known to the market before the uncertainty about patent application is resolved.[6]

Next, we need to choose the length of the announcement window around the patent issuance event. To guide our decision, we examine the pattern of trading volume on the stocks of firms that have been issued a patent. We focus on the ratio of daily volume to shares outstanding. We compute the 'abnormal' share turnover around patent issuance days, after adjusting for firm-year and calendar day effects. As we see in Figure 1, there is a moderate and statistically significant increase in share turnover around the day that the firm is granted a patent – with most of the increase taking place on the first two days following the announcement.[7] In particular, we find that the total abnormal turnover in the first two days after the announcement increases by 0.2%. This is a significant increase when compared to the median daily turnover rate of 1.3%. Even though prices can adjust to new information absent any trading, the fact that stock turnover increases following a patent grant is consistent with the view that patent issuance conveys important information to the market.

In sum, we conclude that two days after the patent issuance seems a reasonable window over which information about successful patent grant is reflected in the stock market. We thus choose a three-day announcement window, $[t,\ t+2]$, for the remainder of our analysis when constructing our measure. As robustness, we also extend the window to five days and obtain quantitatively similar results.

[6] In addition to the patent issuance date, we examined stock price responses around other event dates, specifically, application filing and publication dates. We find no significant stock price movements around application filing dates, consistent with the fact that the USPTO does not publish applications at the time they are filed. After 2000, the USPTO started publishing applications eighteen months after the filing date. We find some weak stock price movements around application publication dates. Since publication-day announcements only occur in the post-2000 period, we do not include the information from these dates since we did not want the statistical properties of the measures to be different across periods.

[7] Our estimates imply that trading volume is temporarily lower prior to the patent issuance announcement. A potential explanation is the presence of increased information asymmetry, with investors worrying about trading against potentially informed insiders who might know more about an impending patent issuance. Similar patterns in trading volume have been documented before earnings announcements, see e.g., Lamont and Frazzini (2007).

1.3 Some Illustrative Examples

Before turning to our main analysis, we first examine some illustrative case studies to study the relation between the stock market reaction and important patent grants. For these examples we performed an extensive search of online and print news sources to confirm that no other news events are likely to account for the return around the patent dates.

The first example is patent 4,946,778, titled "Single Polypeptide Chain Binding Molecules", which was granted to Genex Corporation on August 7, 1990. The firm's stock price increased by 67 percent (in excess of market returns) in the three days following the patent announcement. Investors clearly believed the patent was valuable, and news of the patent was reported in the media. For example, on August 8 *Business Wire* quoted the biotechnology head of a Washington-based patent law firm as saying "The claims issued to Genex will dominate the whole industry. Companies wishing to make, use or sell genetically engineered SCA proteins will have to negotiate with Genex for the rights to do so." The patent has subsequently proved to be important on other dimensions as well. The research that developed the patent, Bird, Hardman, Jacobson, Johnson, Kaufman, Lee, Lee, Pope, Riordan, and Whitlow (1988), was published in *Science* and has since been cited over 1300 times in Google Scholar, while the patent itself has been subsequently cited by 775 patents. Genex was acquired in 1991 by another biotechnology firm, Enzon. News reports at the time indicate that the acquisition was made in particular to give Enzon access to Genex's protein technology. Another example from the biotechnology industry is patent 5,585,089, granted to Protein Design Labs on December 17, 1996. The stock rose by 22 percent in the next two days on especially high trading volume. On December 20, the *New York Times* reported that the patent "could affect as much as a fourth of all biotechnology drugs currently in clinical trials."

As another illustration, consider the case of patent 6,317,722 granted to Amazon.com on November 13, 2001 for the "use of electronic shopping carts to generate personal recommendations". When Amazon filed this patent in September 1998, online commerce was in its infancy. Amazon alone has grown from a market capitalization of approximately $6 billion to over $100 billion today. The importance of a patent that staked out a claim on a key part of encouraging consumers to buy more – the now-pervasive "customers also bought" suggestions– was not missed by investors: the stock appreciated by 34 percent in the two days after the announcement, adding $900 million in market capitalization.

Our methodology is potentially helpful in distinguishing between innovations that are scientifically important and those that have a large impact on firm profits. For example, consider patent 6,329,919 granted to IBM in 2001 for a "system and method for providing reservations for restroom use." This patent describes a system to allow passengers on an airplane to reserve a spot in the bathroom queue. The patent has subsequently been of such little value to IBM that the firm has stopped paying the annual renewal fee to the USPTO, and the patent has now lapsed. Our method would identify this patent as having little economic value – the return over the 3-day window is slightly negative, and there is no change in the trading volume. By contrast, citation counts indicate that this patent presented a considerable scientific advance – the patent has received 21 citations, which places it in the top 20% of the patents granted in the same year.

1.4 Estimating the Value of a Patent

The second step in constructing our measure is to isolate the component of firm return around patent issuance events that is related to the value of the patent. In particular, the stock price of innovating firms may fluctuate during the announcement window around patent issuance for reasons unrelated to innovation. Hence, it is important to account for measurement error in stock returns.

To remove market movements, we focus on the firm's idiosyncratic return defined as the firm's return minus the return on the market portfolio.[8] We decompose the idiosyncratic stock return R for a given firm around the time that its patent j is issued as

$$R_j = v_j + \varepsilon_j, \tag{2}$$

where v_j denotes the value of patent j – as a fraction of the firm's market capitalization – and ε_j denotes the component of the firm's stock return that is unrelated to the patent.

We construct our estimate ξ of the economic value of patent j as the product of the estimate of the stock return due to the value of the patent times the market capitalization M of the firm that is issued patent j on the day prior to the announcement of the patent issuance:

$$\xi_j = (1 - \bar{\pi})^{-1} \frac{1}{N_j} E[v_j | r_j] \; M_j. \tag{3}$$

If multiple patents N_j are issued to the same firm on the same day as patent j, we assign each patent a fraction $1/N_j$ of the total value. Since the unconditional probability $\bar{\pi}$ of a successful patent application is approximately 56% in the 1991-2001 period (see, e.g. Carley, Hegde, and Marco, 2014), we account for this understatement by multiplying our estimates of patent values by $1/0.44 = 2.27$.[9]

[8]By using this 'market-adjusted-return model' (Campbell, Lo, and MacKinlay, 1997), we avoid the need to estimate the firm's stock market beta, therefore removing one source of measurement error. As a robustness check, we construct the idiosyncratic return as the firm's stock return minus the return on the beta-matched portfolio (CRSP: bxret). This has the advantage that it relaxes the assumption that all firms have the same amount of systematic risk, but is only available for a smaller sample of firms. Our results are quantitatively similar when using this alternative definition.

[9]In principle, the ex-ante probability of a successful patent grant π_j could vary with the private value of a patent ξ. This possibility will induce measurement error in the estimated patent values. Aggregating patent values within a firm (or year) will partly ameliorate this concern, as long as the joint distribution of π and ξ is stable within firm-years. However, this need not be the case. Carley et al. (2014) use proprietary data

To implement (3), we need to make assumptions about the distributions of v and ε. We allow both distributions to vary across firms f and across time t. Since the market value of the patent v is a positive random variable, we assume that v is distributed according to a normal distribution truncated at zero, $v_j \sim \mathcal{N}^+(0, \sigma^2_{vft})$.[10] Further, we assume that the noise term is normally distributed, $\varepsilon_j \sim \mathcal{N}(0, \sigma^2_{\varepsilon ft})$. Given our assumptions, the filtered value of v_j as a function of the idiosyncratic stock return R is equal to

$$E[v_j|R_j] = \delta_{ft}\, R_j + \sqrt{\delta_{ft}}\, \sigma_{\varepsilon ft}\, \frac{\phi\left(-\sqrt{\delta_{ft}}\, \frac{R_j}{\sigma_{\varepsilon ft}}\right)}{1 - \Phi\left(-\sqrt{\delta_{ft}}\, \frac{R_j}{\sigma_{\varepsilon ft}}\right)}, \tag{4}$$

where ϕ and Φ are the standard normal pdf and cdf, respectively, and δ is the signal-to-noise ratio,

$$\delta_{ft} = \frac{\sigma^2_{vft}}{\sigma^2_{vft} + \sigma^2_{\varepsilon ft}}. \tag{5}$$

The conditional expectation in (4) is an increasing and convex function of the idiosyncratic firm return R. The exact shape of this function depends on the distributional assumptions for v and ε.[11]

To proceed further, we need to estimate the parameters $\sigma_{\varepsilon ft}$ and σ_{vft}. If we allow both variances to arbitrarily vary across firms and across time, the number of parameters becomes quite large and thus infeasible to estimate. We therefore specify that the signal-to-noise ratio is constant across firms and time, $\delta_{ft} = \delta$. This assumption implies that $\sigma^2_{\varepsilon ft}$ and σ^2_{vft} are allowed to vary across firms and time, but in constant proportions to each other. To estimate

from USPTO and document that the point estimates of the acceptance rates varied between 50% and 60% in the 1991-2001 period. This possibility implies that our firm and aggregate level innovation measures should be interpreted with caution. Obtaining an estimate of the ex-ante probability π at the firm-year level over the horizon of our sample is challenging because data on patent applications – required to construct π – are publicly available only post-2000. In addition, even during post-2000 period, this data contains unreliable information on assignee names that is required to match the patents to firms. We return to this issue in Section 3.2 below.

[10] We are grateful to John Cochrane for this suggestion.

[11] We experimented with different distributional assumptions for v and ε. We relegate the details to the Online Appendix. We, (i) allowed for a non-zero mean for the truncated normal; (ii) we modeled v as an exponential distribution; and (iii) we modeled v and ϵ as following a truncated Cauchy and a standard Cauchy distribution, respectively. The resulting estimates of patent values were quite similar: in the first case, allowing for a non-zero mean had mostly a scaling effect on our estimates: the correlation of filtered returns (4) was in excess of 99%. To obtain a more meaningful difference we would have to allow for the unconditional mean of v_j to vary across firm-years. This is difficult to do since daily data on stock returns are not very informative about the mean of the value of the patent. In cases (ii) and (iii) the correlation between the filtered returns under these additional distributional assumptions ranges from 84% to 89%. In an earlier version of the paper, we also approximated (4) with a piecewise linear function, $\max(0, R)$; the correlation between this approximation and our filtered returns (4) was approximately equal to 48%. In the Online Appendix, we repeat the main parts of the analysis in the paper using measures constructed under these alternative distributional assumptions. The results are comparable, as we can see in Online Appendix Tables (A.7) and (A.8).

δ, we compute the increase in the volatility of firm returns around patent announcement days. Specifically, we regress the log squared returns on a patent issue-day dummy variable, I_{fd},

$$\log{(R_{fd})}^2 = \gamma I_{fd} + c\, Z_{fd} + u_{fd}, \tag{6}$$

where R_{fd} refers to the 3-day idiosyncratic return of firm f, starting on day d. In this estimation, we restrict the sample to firms that have been granted at least one patent. We include controls Z for day-of-week and firm interacted with year fixed effects to account for seasonal fluctuations in volatility and the fact that firm volatility is time-varying. The signal-to-noise estimate can be recovered from the estimated value of γ using $\widehat{\delta} = 1 - e^{-\widehat{\gamma}}$. Our estimate $\widehat{\gamma} = 0.0146$ implies $\widehat{\delta} \approx 0.0145$, so we use this as our benchmark value.[12] The last step in estimating (4), involves estimating the variance of the measurement error $\sigma^2_{\varepsilon f t}$. We do so non-parametrically using the sum of squared market-adjusted returns, and we allow the estimate to vary at an annual frequency (see, e.g. Andersen and Terasvirta, 2009).[13]

Last, one important caveat is that our estimation of δ implicitly assumes that the market does not revise its beliefs about the value of the patent at the time the patent is issued. This assumption is valid post-2000, under the view that market has the same expertise as the USPTO in evaluating the patent given the same information set. Specifically, subsequent to the American Inventors Protection Act, which became effective on November 30, 2000, the USPTO began publishing patent applications 18 months after the filing date, even if the patents had not yet been granted. Hence, for these applications, the market should have had full knowledge of the value of the patent at the time of the patent grant. However, prior to 2000, patent applications were only disclosed to the public at the time the patents were granted to firms. Hence, it is possible that during the period prior to 2000, the market did not know the full value of the patent prior to the patent being granted. If this were the case, then the increase in stock market volatility following a patent grant likely overestimates δ, since it also includes movements in stock prices that are related to revisions of the patent value.[14]

[12] We also experimented with allowing γ to vary by firm size; except for the smallest firms, the estimates of γ were statistically similar across firm size quintiles.

[13] In particular, we first estimate the conditional volatility of firm f at year t using the realized mean idiosyncratic squared returns, σ^2_{ft}. This second moment is estimated over both announcement and non-announcement days, so it is a mongrel of both σ^2_{vft} and $\sigma^2_{\varepsilon ft}$. Given our estimate of σ^2_{ft}, the fraction of trading days that are announcement days, d_{ft}, and our estimate $\widehat{\gamma}$, we recover the variance of the measurement error through $\sigma^2_{\varepsilon ft} = 3\,\sigma^2_{ft}\,\left(1 + 3\, d_{ft}\,(e^{\hat{\gamma}} - 1)\right)^{-1}$.

[14] Specifically, if the market also updates its beliefs about ξ, the change in the stock price at the grant date would be equal to

$$\Delta V_{jt} = (1 - \pi_j)\,\xi_j + \pi\,(\xi_j - \hat{\xi}_j),$$

where $\hat{\xi}$ is the prior belief about the market value of the patent. Assuming the forecast error $\xi_j - \hat{\xi}_j$ is uncorrelated with the value of the patent, equation (2) still applies. However, we can no longer use (6) to estimate δ.

To examine the importance of this issue, we exploit the change in information disclosure policy by the American Inventors Protection Act (AIPA) that applied to all patents filed after November 30th 2000. For the patents that were filed after November 30th 2000 – and whose publication date occurred 18 months after the application date, but before the grant date – the market had full knowledge of their quality at the time these patents were granted. By contrast, for the patents filed before November 30th, it is possible that on the grant day the stock market reaction indeed contains news about the market value of the patent, ξ. To assess if this possibility impacts our estimation, we compare estimates of the signal-to-noise ratio using (6) across the two sets of patents: patents that were filed just before the act, that is in the month of November 2000; and patents that were filed immediately after the act, that is in December 2000. Using stock price reactions around the grant dates of these patents we find that the point estimate of γ is 0.03 *larger* for the patents filed in December 2000 relative to the patents filed in November 2000. However, the difference is not statistically significant (p-value is 0.31). We interpret this evidence as suggesting that the information content around the application publication date may be small and as a result we do not alter the estimation of the signal-to-noise ratio δ.[15]

1.5 Descriptive Statistics

In Table 1 we report the sample distribution of ξ along with other variables: the number of forward citations, the idiosyncratic firm returns R_f, and filtered patent values obtained from (4). As is well known, the distribution of patent citations is highly skewed, with approximately 16% of patents receiving zero citations. In addition, the distribution of firm returns R_f is right skewed, and positive roughly 55 percent of the time. In addition, the estimated value of patents – both in absolute terms ξ as well as relative to the firm market capitalization (4) – is also highly skewed.

Our procedure delivers a median value of a patent equal to \$3.2 million in 1982 dollars. Given the scarcity of data on the value of innovations, the plausibility of this number is difficult to assess. One point of comparison is Giuri et al. (2007) who conduct a survey of inventors for a sample of 7,752 European patents. The inventors were asked to estimate the *minimum* price at which the owner of the patent, whether the firm, other organizations, or the inventor himself, would have sold the patent rights on the day on which the patent was granted. Giuri et al. (2007) report that about 68% of all the patents in their sample have a (minimum) value of less than 1 million Euros.

Given those estimates, the average level of patent values seems a bit high. However, we should note that our estimates are based on a sample of public firms; these firms may

[15] Nevertheless, we do investigate the robustness of our results to different values of δ. As noted above, in the presence of information about the patent quality that is also revealed on grant date, our estimate of the signal-to-noise ratio δ *underestimates* the amount of noise. We thus repeat our empirical analysis using smaller estimates of δ. Our findings are economically similar and are available upon request.

attach higher valuations to individual patents compared to the inventors of the sample in Giuri et al. (2007). In addition, the distributional assumptions we made in equation (4) likely also play a role. In particular, the mean of the distribution of v_j is closely tied to the second moment of v_j.[16] Further, we have scaled our estimated patent values by the average acceptance probability $\bar{\pi}$ in the 1991-2001 subsample. If the ex-ante acceptance probability is correlated with patent values, this will bias the estimate of the average patent value upwards. Last, another possibility that could inflate the estimated patent values is that a patent grant may sometimes provide information about the likelihood of future patents being granted.

In sum, even if the average valuation is too high, cross-sectional differences in value across patents can still be meaningful. Thus, we next explore whether our measure correlates with the other commonly used measure of patent quality, forward citations.

2 Patent Market Values and Citations

The relation between the private and the scientific value of innovation has been the subject of considerable debate. The innovation literature has argued that forward patent citations are a good indicator of the 'quality' of the innovation. Hall et al. (2005) and Nicholas (2008) have argued that forward citations are also correlated with the private value of patents based on a regression of a firms Tobin's Q on its stock of citation-weighted patents. Harhoff et al. (1999) and Moser et al. (2011) provide estimates of a positive relation using smaller samples that contain estimates of economic value. However, the relation between patent citations and the private value of a patent can be theoretically ambiguous. Abrams et al. (2013) cast doubt on these earlier findings by proposing a model of defensive patenting. Using a proprietary dataset that includes estimates of patent values based on licensing revenues, they document an inverse-U relation between citations and patent values.

Armed with our measure, we re-examine the relation between citations and the market value of innovation using the number of citations that the patent receives in the future. Our measure allows us to study this question at a more granular level than Hall et al. (2005), while using a broader sample than Abrams et al. (2013). We relate the total number of citations C a patent j receives in the future to the estimated value of the patent, ξ_j,

$$\log \xi_j = a + b \log (1 + C_j) + c\, Z_j + u_j. \tag{7}$$

To control for omitted factors that may influence citations and the measured patent valuations, we include a vector of controls Z that includes: grant-year fixed effects, because older patents have had more time to accumulate citations; the firm's log market capitalization $\log M_j$

[16] For instance, allowing the mean of the distribution of v_j (before truncation) to vary from zero resulted in somewhat smaller magnitudes for patent values (median of 1.8 million). However, doing so has only a scaling effect on our estimate of patent values.

(measured on the day prior to the patent grant), as larger firms may produce more influential patents; the firm's log idiosyncratic volatility $\log \sigma_{ft}$, since it mechanically affects our measure while at the same time fast-growing firms have more volatile returns and could produce higher quality patents; technology class-year fixed effects, since citation numbers may vary across different technologies over time; and firm fixed effects to control for the presence of unobservable firm effects. Last, we also estimate a specification with firm effects interacted with year, to account for the possibility that these unobservable firm effects may vary over time. We cluster the standard errors by grant year to account for potential serial correlation in citations across patents granted in a given year.

We present the results in Table 2. Consistent with the findings of Harhoff et al. (1999) and Hall et al. (2005), we find a strong and positive association between forward citations and market values. Figure 2 summarizes the univariate relation between citations and patent market values. To plot it we group the patent data into 100 quantiles based on their patent citations, scaled by the mean number of citations to patents in the same year cohort. We then plot the average number of cohort-adjusted patent citations in each quantile versus the mean of the estimated patent value in each quantile, also scaled by the mean estimate of all patents in the same year cohort. We see that this relation is monotonically increasing, and mostly log-linear, with the possible exception of patents with very few citations.[17] This pattern is somewhat at odds with the findings of Abrams et al. (2013), who document an inverse-U relation between citations and value of patents. We conjecture that this discrepancy may be due to differences in our sample relative to that used in Abrams et al. (2013).

The economic magnitudes implied by our estimates are comparable to those obtained by the existing literature. One additional forward citation, around the median number of citations, is associated with a 0.1% to 3.2% increase in the value of that patent, depending on the controls included. For comparison, Hall et al. (2005) find that, relative to the median, if all the firm's patents were to have one additional cite, this increase would be associated with an increase in the value of the firm by approximately 3%. A further point of comparison is Harhoff et al. (1999), who study the relation between survey-based estimates of patent values and citations for a sample of 962 patents. Their estimates imply that a single citation around the median is associated with, on average, more than \$1 million of economic value. Evaluated at the mean of the distribution of ξ_j, our estimates imply that one additional citation around the median number of citations in our sample is associated with approximately 15 to 500 thousand US dollars (in 1982 prices).

In sum, our innovation measure ξ is economically meaningfully related to future citations. This fact, combined with the previously documented links regarding patent citations and

[17] As Table 1 shows, a quarter of patents in our sample receive either zero or one citation in the future. The discreteness of citation counts makes it difficult to differentiate among these patents. In contrast, our measure indicates some variation in quality among these less-cited patents. The non-linearity at the bottom end of the citations distribution partly reflects this fact. Further, citations occur with a lag, implying that this discreteness problem will be accentuated for more recent patents.

market value, can be interpreted as a test of external validity for our measure. Along these lines, we performed a series of placebo experiments to illustrate that the relation between value of a particular patent and the number of citations received by that patent in the future is not spurious. In each placebo experiment, we randomly generate a different issue date for each patent within the same year the patent is granted to the firm. We repeat this exercise 500 times and then reconstruct our measure using the placebo grant dates. In Figure 3, we plot the distribution of the estimated coefficients and t-statistics corresponding to the specification in column (5) of Table 2. Based on the distribution of coefficients and t statistics across the placebo experiments, centered at zero, relative to the effects we find in Table 2, we conclude that our results are unlikely to be spurious.

Importantly, we want to reiterate that our innovation measure ξ and forward patent citations likely measure different aspects of quality. By construction, our procedure aims to measure the private economic value of a patent. Patent citations are more reflective of the scientific value of the innovation. For instance, one patent may represent only a minor scientific advance – and thus receive few citations – but be particularly successful at restricting competition and thus generate sizeable private benefits. With that distinction in mind, we show in the next section that our measure also contains information about future firm growth that is distinct from that included in patent citations.

3 Innovation and Firm Growth

Models of endogenous growth have rich testable predictions about the cross-section of firms, linking improvements in the technology frontier to resource reallocation and subsequent economic growth (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004). Since the value of a firm's innovative output is hard to observe, constructing direct empirical tests of these models has proven challenging. Here, we use our estimate of the value of innovation to examine the predictions of these models. We will also contrast the dynamics of reallocation and growth using our measure with the citations based measure that is available in the literature.

3.1 Firm-level measures of innovation

We merge our patent data with the CRSP/Compustat merged database. We restrict the sample to firm-year observations with non-missing values for book assets and SIC classification codes. We also omit firms in industries that never patent in our sample. In addition, we omit financial firms (SIC codes 6000 to 6799) and utilities (SIC codes 4900 to 4949), leaving us with 158,739 firm-year observations that include 15,787 firms in the 1950 to 2010 period. Out of these firms, only one third (5,801 firms) file at least one patent. To minimize the impact of outliers, we winsorize all variables at the 1% level using yearly breakpoints.

We first measure the total dollar value of innovation produced by a given firm f in year t, based on stock market (sm), by simply summing up all the values of patents j that were granted to that firm,

$$\Theta_{f,t}^{sm} = \sum_{j \in P_{f,t}} \xi_j, \tag{8}$$

where $P_{f,t}$ denotes the set of patents issued to firm f in year t. A highly popular measure of the output of innovation produced by a firm is its citation-weighted (cw) patents. We thus constrict an analogous measure using this metric,

$$\Theta_{f,t}^{cw} = \sum_{j \in P_{f,t}} \left(1 + \frac{C_j}{\bar{C}_j}\right) \tag{9}$$

where $\bar{C}_j$ is the average number of forward citations received by the patents that were granted in the same year as patent j. This scaling is used to adjust for citation truncation lags (Hall et al. (2005)). Both (8) and (9) are essentially weighted patent counts; if firm f files no patents in year t, both variables are equal zero.

Large firms tend to file more patents. As a result, $\Theta_{f,t}^{sm}$ and $\Theta_{f,t}^{cw}$ are strongly increasing in firm size (see Online Appendix Table A.3). In our analysis, we need to ensure that fluctuations in size are not driving the variation in innovative output. We therefore scale the two measures above by firm size. We use book assets as our baseline case,

$$\theta_{f,t}^{m} = \frac{\Theta_{f,t}^{m}}{B_{ft}}, \tag{10}$$

for $m \in \{sm, cw\}$, where B_{ft} is book assets of firm f in year t. We note that our inferences in the analysis that follows are not sensitive to using book assets for normalization since we also control for various measures of firm size in all our specifications. As we discuss below, the results using our measure are similar if we scale by the firm's market capitalization instead.

Table 3 presents summary statistics related to the two measures of innovation, $\theta_{f,t}^{sm}$ and $\theta_{f,t}^{cw}$. Innovative activity is highly skewed across firms – as captured by both our measure and citation-weighted patents. This is consistent with the prior literature that has noted that most firms do not patent and that there is large dispersion in the number of citations across patents. Examining the next rows of Table 3, we note that there is substantial heterogeneity in firm growth rates of output, profits as well as capital and labor. Further, there is substantial heterogeneity in mean innovation outcomes across industries (see Online Appendix, Table A.5). The most innovative industries are Drugs, Automobiles and Chemicals while least innovative ones are Food, Tobacco and Apparel/Retail. These patterns match those of innovators as described by Baumol (2002), Griliches (1990) and Scherer (1983). In addition, there is some interesting time series variation in the distribution of innovation outcomes across firms (see Online Appendix, Table A.4). In particular, we see an increase in dispersion of innovative output, with an increase in both the mass of firms that do not patent as well, as an increase in the value of innovative output at the extreme end.

3.2 Firm Innovation, Growth and Productivity

We now examine the relation between innovation and firm growth and productivity. Endogenous growth models imply that firm growth is related to innovation, typically measured by the number of product varieties or the quality of goods the firm is producing (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004). In a majority of these models, innovation by other firms has a negative impact on firm growth, either directly through business stealing or indirectly through changes in factor prices. We refer to the latter effect as creative destruction.

Methodology

To examine creative destruction, we need to compute a measure of innovation by competing firms. We define the set of competing firms as all firms in the same industry – defined at the SIC3 level– excluding firm f. We denote this set by $I \setminus f$. We then measure innovation by competitors of firm f as the weighted average of the innovative output of its competitors,

$$\theta^i_{I\setminus f,t} = \frac{\sum_{f'\in I\setminus f} \Theta^i_{f',t}}{\sum_{f'\in I\setminus f} B_{f't}}. \tag{11}$$

We compute (11) for both the market based measure (sm) as well as for citation-weighted patent counts (cw).

We assess the relation between the innovative activity of the firm and its competitors and its future growth and productivity. In particular, as dependent variables, X, we iteratively use (a) profits, (b) nominal value of output, (c) capital stock, (d) number of employees and (e) revenue-based productivity (TFPR). We estimate the following specification.

$$\log X_{f,t+\tau} - \log X_{f,t} = a_\tau\, \theta_{f,t} + b_\tau\, \theta_{I\setminus f,t} + c\, Z_{ft} + u_{ft+\tau}. \tag{12}$$

We explore horizons τ of 1 to 5 years. In addition to X_{ft}, the vector Z includes the log value of the capital stock and the log number of employees to alleviate our concern that firm size may introduce some mechanical correlation between the dependent variable and our innovation measure. For instance, large firms tend to innovate more, yet have been shown to grow slower (see e.g., Evans, 1987). Controlling for other measures of size (i.e. book assets) yields similar results. We control for firm idiosyncratic volatility σ_{ft} because it may have a mechanical effect on our innovation measure and is likely correlated with firms' future growth opportunities (Myers and Majluf, 1984). Last, we include industry and time dummies to account for unobservable factors at the industry and year level. We cluster standard errors by both firm and year. To facilitate the comparison between our measure and patent citations, we normalize both variables to unit standard deviation.

Estimation Results

We focus on the estimates of a and b, which capture the direct impact of firm innovation on growth and the degree of creative destruction, respectively. Panels (a) to (d) of Table 4 examine firm growth, as measured by the growth rate of (a) profits, (b) nominal output, (c) capital and (d) number of employees. Consistent with models of innovation, we see that future firm growth is strongly related to the firm's own innovative output. The magnitudes are substantial; over a five-year horizon, a one standard deviation increase in firm's innovation is associated with a 4.6% increase in profits, a 3.2% increase in output, a 3.8% increase in capital investment, and a 2.5% increase in employment.

Our estimates of b suggest that innovation is associated with a substantial degree of creative destruction. In particular, a one standard deviation increase in innovation by firm's competitors is associated with a decline of 3.8% in profits, 5.1% in output, 3.8% in capital investment and 2.7% in employment, over the same five-year horizon. Relative to existing studies that study externalities associated with firm innovation (e.g. Bernstein and Nadiri, 1989; Bloom et al., 2013) our estimates imply a substantially higher degree of creative destruction. We conjecture that this difference is likely due to the fact that θ^{sm} – by construction – measures the *private* value of innovation – as opposed to its social value, which may include research-related externalities. We revisit this issue below when we compare our results to those using citation-weighted patent counts.

Panel (e) of Table 4 examines the relation between innovation and (revenue-based) firm productivity. We see that a one standard deviation increase in firm's innovation is associated with a 2.4% increase in firm's revenue-based productivity. Conversely, a one standard deviation increase in innovation by firm's competitors is followed by a 1.7% drop in productivity over five years. The negative effect of competitor innovation on revenue-based productivity is most likely due to its negative effect on firm-level prices, possibly due to business-stealing effects.[18]

Overall, our measure of innovation activity is related to firm growth and productivity, providing direct support for models of endogenous growth. In addition, these results contribute to the discussion on the determinants of growth rates and productivity differences across firms. Understanding why these differences exist – and persist over time – and relating them to specific aspects of firms' economic activity remains a significant challenge.[19] A direct

[18]For instance, if the firm is producing a portfolio of patented and non-patented goods, and having a patent allows the firm to act as a monopolist and charge a higher markup, the loss of a good to a rival firm could imply that the firm's average markup – across all goods it produces – falls. In this case, we would see a drop in TFPR.

[19]See, for example Syverson (2011); Haltiwanger (2012). While some of the measured differences likely reflect imperfections in the measurement in productivity, they also reflect, to a large degree, real differences in firms' ability to generate revenue for given capital and labor inputs.

measure of the firm's innovative output allows us to quantify the strength of this relation. In this respect, our approach is similar to Bloom and Van Reenen (2007) who document that differences in their measure of management quality across firms account for a significant fraction of dispersion in TFP across firms.[20]

Comparison to citation-based measures

We next compare the results above to those obtained using a more traditional measure of innovative output, citation-weighted patents. Table 5 reports estimates of (12) using the citation-based measure θ^{cw}. Examining the response of future growth and productivity to own innovation, we again see a strong positive association. Comparing these estimates of a to those of Table 4, we note that they are smaller in magnitude, typically less than half. Specifically, a one standard deviation change in firm's innovation, as measured using citations-weighted patents, is associated with a 2.5% increase in profits, 1.9% increase in output, 1.5% increase in capital investment, 1.5% increase in employment and a 1% increase in productivity. These smaller magnitudes are not surprising, since firm investment decisions are related to the private value of innovation, which may be imperfectly reflected in the number of citations to the patent.

More importantly, the results in Table 5 reveal no evidence for creative destruction. The estimated coefficients b are either positive or not statistically different from zero. The stronger pattern of creative destruction associated with θ^{sm} is consistent with our conjecture above that our measure is more highly correlated with the private value of a patent relative to patent citations. Citations on the other hand are more likely to be correlated with the scientific value of a patent and thus more accurately measure the impact of research externalities.

Last, we explore whether our measure and patent citations contain independent information about future firm growth. That is, we re-estimate (12) including both θ^{sm}_f and θ^{cw}_f, as well as $\theta^{sm}_{I\setminus f}$ and $\theta^{cw}_{I\setminus f}$. We report the estimation results in Table 6. We see that the relation between θ^{sm} and future firm growth and productivity is comparable to those in Table 4. By contrast, the relation between the citation-based measure and own firm growth is in many cases not statistically different from zero. By design, our measure and citation-weighted patent counts should contain independent information regarding externalities. Examining the right panel of Table 6 we note a strong negative effect of competitor innovation on firm growth and productivity measured using value-weighted patent counts (θ^{sm}) and a positive effect when innovation output is measured using citation-weighted patent counts (θ^{cw}).

[20] A direct comparison between our results and Bloom and Van Reenen (2007) is difficult because their management quality measure is a stock measure, while our innovation measure is a flow measure. Specifically, (Bloom and Van Reenen, 2007) find that spanning the interquartile range of the management score distribution, for example, corresponds to a productivity change of between 3.2 and 7.5 percent, which is between 10 and 23 percent of the interquartile range of TFP in their sample.

In sum, these findings allow us to draw two conclusions. First, there is additional information about the quality of innovation in our measure than what is captured in citations. This additional information is most likely related to private values of a patent. Depending on the intended application, one measure may be more useful than the other.[21] Second, using our estimate of the private value of innovation, we document substantial patterns of creative destruction relative to those previously documented.

Robustness and Caveats

The estimated value of innovative output $\theta^{sm}_{f,t}$ contains information on the firm's market valuation in the numerator, but not in the denominator. Hence, one potential concern is that fluctuations in $\theta^{sm}_{f,t}$ simply reflect fluctuations in the market valuation of firm f rather than the value of the innovative output of firm in year t. To address this concern, we replace the book value of assets in the denominator of $\theta^{sm}_{f,t}$ with the firm's stock market capitalization at the end of year t. We find that doing so leads to similar results, although they are smaller in magnitude by about one-third (see Table A.9 in the Online Appendix). Second, market values are measured at a point in time, while citations are measured throughout the entire sample. As a robustness check, we verify that results are similar when we only measure citations within the first few years after the patent is granted (see Table A.10 in the Online Appendix). A third caveat is that the relation between innovation and firm growth we document is based on correlations and cannot be interpreted causally. For instance, fast-growing firms may invest more in R&D and thus also innovate more, but innovation may be unrelated to firm growth. We found that including controls for R&D spending did little to alter the magnitude of the estimated coefficients a and b (Table A.11 in the Online Appendix). Fourth, it is possible that our measure simply captures fluctuation in investor attention; if investors pay attention to fast growing firms, this could explain our results. We found that controlling for three proxies for investor attention – the number of times the firm is mentioned in the Wall Street Journal, the number of analyst coverage, and the fraction of institutional ownership – did little to affect the economic and statistical significance of our results (Table A.12 in the Online Appendix).

More generally, we measure the private value of innovative output with substantial measurement error. In particular, as we can see from equation (1), this measurement error depends on the ex-ante likelihood of the patent being granted.[22] We cannot rule out the possibility that this measurement error covaries with unobservable factors that also determine firm growth. To partly alleviate these concerns, we use the R&D price variable constructed

[21] We could extend our methodology to estimate the value of a patent including its effect on competing firms, using the competitors' stock market reaction. This measure could be closer to the 'social value' of innovation. We leave this task for future research.

[22] Estimating the ex-ante likelihood of a patent grant requires information on patent applications. As noted earlier, such data is only available post-2001. However, as of 2015, there is no reliable publicly available assignee information in these patent applications.

by Bloom et al. (2013) as an instrument. This R&D price is constructed at an annual level for each firm using state-level R&D tax credits. This price varies across firms because different states have different levels of R&D tax credits and corporation tax, which will differentially affect firms depending on their cross-state distribution of R&D activity. In addition, we construct an R&D price for competing firms in a similar manner to equation (11), that is, equal to the average R&D price of firms competing with firm f. We then use the firm and competitor R&D price to instrument for θ_f and $\theta_{I \setminus f}$ when estimating equation (12). The first-stage regression reveals a strong, negative, relation between the firm- and competitor R&D price and firm and competitor innovation outcomes, respectively. Importantly, the second-stage estimates are qualitatively similar to our baseline results, thought the magnitudes are stronger (see Table A.13 in the Online Appendix).

4 Aggregate Effects of Innovation

Here, we assess the role of technological innovation in accounting for medium-run fluctuations in aggregate economic growth and TFP. A notable challenge facing real business cycle models is the scarcity of evidence linking movements in TFP to clearly identifiable measures of technological change. At the aggregate level, whether technological innovation is socially valuable in endogenous growth models depends on the degree to which it contributes to aggregate productivity – as opposed to simply being a force for reallocation and creative destruction. If the creative destruction effects dominate, an increase in aggregate innovation activity would lead to resource reallocation across firms but only minor increases in output.

We tackle this question in two ways. First, the results in the previous section illustrate that an increase in a firm's innovative output is associated with higher growth and productivity; by contrast, innovation by competing firms has the opposite effect. In Section 4.1, we use firm-level estimates of Section 3.2 to examine the net impact of innovation on aggregate output and productivity. Second, in Section 4.2, we propose an aggregate index of innovation activity – that is based on a simple model of innovation – and relate the index to aggregate output and productivity.

4.1 Aggregating coefficients

As a first step in assessing the net impact of innovation, we examine what our empirical estimates in Section 3.2 imply about the net effect of innovation within our sample of publicly traded firms. To do so, we need to compare the relative magnitudes of the estimated coefficients a and b in equation (12). However, since the equation is expressed in terms of growth rates, we cannot determine the sign and the magnitude of the net effect by simply comparing the two coefficients a and b.

We thus proceed as follows. We first compute the portion of the dollar change in the size X of firm f between time t and $t+\tau$ that is associated with its own innovation and the innovation by other firms in the same industry as

$$\hat{X}_{f,t+\tau} - \hat{X}'_{f,t+\tau} = \left[\exp\left(\hat{a}_\tau\, \theta_{ft} + \hat{b}_\tau\, \theta_{I\setminus ft} + \hat{c}_\tau\, Z_{ft}\right) - \exp\left(\hat{c}_\tau\, Z_{ft}\right)\right]\, X_{f,t}, \tag{13}$$

where we have made explicit the dependence of the estimated regression coefficients on the horizon, τ. Here, we use the notation X' to refer to the counterfactual level of X in the case in which our measure is uniformly equal to zero. Second, we aggregate these estimates across all firms in the sample to obtain the average component of aggregate growth related to innovation,

$$\hat{G}_\tau = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{\tau}\frac{\sum_f \left(\hat{X}_{f,t+\tau} - \hat{X}'_{f,t+\tau}\right)}{\sum_f X_{f,t}}\right], \tag{14}$$

In equation (14), the numerator and denominator sum across all firms that survive to time τ. The sample mean of $\hat{G}_{t,t+\tau}$ can be interpreted as the annual aggregate growth rate between periods t and $t+\tau$ that is related to firm innovation, subject to two caveats: i) we omit some general equilibrium effects due to the presence of time dummies in equation (12) and ii) our estimate aggregates outcomes within our sample of public firms.

Similarly, we can define an index of creative destruction in a manner analogous of excess reallocation (using the definition of Davis, Haltiwanger, and Schuh, 1998), as

$$\hat{D}_\tau = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{\tau}\frac{\sum_f |\hat{X}_{f,t+\tau} - \hat{X}'_{f,t+\tau}|}{\sum_f X_{ft}} - |\hat{G}_{t,t+\tau}|\right] \tag{15}$$

Equation (15) measures the degree of cross-sectional volatility in growth rates that is related to innovation. To assess the magnitudes of (14) and (15) we can compare them to their realized counterparts,

$$G_\tau = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{\tau}\frac{\sum_f [X_{f,t+\tau} - X_{f,t}]}{\sum_f X_{f,t}}\right] \tag{16}$$

and

$$D_\tau = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{\tau}\frac{\sum_f |X_{f,t+\tau} - X_{f,t}|}{\sum_f X_{ft}} - |G_{t,t+\tau}|\right]. \tag{17}$$

When comparing our aggregate estimate of reallocation (15) to its realized counterpart (17), note that $\hat{D}_\tau$ is based on predicted values, hence it is unlikely to capture a substantial fraction of fluctuations in realized firm growth rates, since these are hard to predict.

Our estimates imply that the contribution of innovation to aggregate growth is positive and substantial. To conserve space, we only report the highest value across horizons τ. Our estimate of $\hat{G}_\tau$ implies that our estimate of innovation can account for an average net growth rate of up to 0.8% in firm profits, 0.1% in firm output, 0.7% in capital and 0.1% in the number of employees. Comparing these estimates to the mean aggregate growth rate for the corresponding variables G within our sample of public firms, we find that innovation can account for a fraction of 5% to 23% of net economic growth.

The degree of creative destruction implied by our estimates is also substantial. Our estimates of $\hat{D}$ imply that innovation can account for a mean cross-sectional dispersion of 0.5% in firm profits, dispersion of 0.5% in sales growth rates, 0.3% in growth rates of capital and 0.3% in the change in the number of employees. Comparing these magnitudes to the realized dispersion in firm growth rates, D, we find them to be approximately 6% to 19% of their realized counterparts. Our estimates thus suggest that differences in innovative outcomes can account for a substantial fraction of ex-post differences in firm growth rates.[23]

In sum, our analysis suggests that, in the aggregate, innovation is associated with significant resource reallocation and growth. While this firm level analysis has several appealing features, its findings should be interpreted with caution for at least two reasons. First, our estimates are based on comparing outcomes within a sample of public firms. They omit any effect of innovation by these public firms on private firms in the industry. Second, our empirical specification (12) include time fixed effects to control for unobserved changes in the economic environment that are unrelated to innovation. However, these time effects could also absorb some of the general equilibrium effects of innovation by firms in our sample. We next explore an alternative approach that constructs an aggregate index of innovation that is motivated by an economic model.

4.2 Aggregate Index of Innovation

Here, we construct an economy-wide index of innovation output. To aggregate our firm-level innovation measures to a composite, we need to make particular assumptions about how firm monopoly profits relate to aggregate improvements in TFP. In Appendix A, we provide a simple model of innovation – based on Atkeson and Burstein (2011) – that delivers an approximately linear relation between the two.[24] After discussing the descriptive properties of

[23] We can also similarly aggregate the firm level coefficients we obtained in Section 3.2 using the citation-based measure. We would expect the relation between aggregate innovation and growth to be greater when using citation-weighted patent counts for two reasons. First, citations may include research externalities that need not be captured by our measure. Second, since citations are an imperfect estimate of private value, they underestimate the effect of creative destruction. Both of these effects should in theory imply that citation-weighted patent counts will overestimate the relation between innovation and growth relative to what would be obtained using our measure. However, the empirical evidence is mixed. We find that, when using citation-weighted patent counts, innovation can account for an average net growth rate of up to 0.4% in firm profits, 0.2% in firm output, 0.2% in capital and 0.4% in the number of employees. These estimates are comparable in magnitude to those obtained using our baseline measure. Importantly, the degree of creative destruction implied by the citation-weighted patent measure is essentially zero.

[24] Alternative models of innovation may result in different functional relations between firm profits and aggregate productivity improvements, particularly quality-ladder models with endogenous markups. These models would therefore generate alternative innovation indices. We leave this for future work.

the index, we examine its correlation with measures of aggregate productivity and economic growth.

Methodology

We construct an economy-wide index of innovation as

$$\hat{\chi}_t = Y_t^{-1} \sum_{f \in \mathcal{F}_t} \Theta_{ft}^{sm}. \tag{18}$$

Equation (18) is equal to the sum of the value of all patents granted in year t to the firms in our sample, scaled by aggregate output Y. The construction of the index (18) is motivated by a simple model of innovation, described in Appendix A. In the model, the index (18) is approximately proportional to the productivity (and output) gains from improvements in the aggregate technology frontier.

A potential concern with the index (18) is that its fluctuations may capture movements in 'discount rates', or more generally, fluctuations in the level of stock prices that are unrelated to fundamentals. To address this concern, we also construct an alternative index, in which instead of output Y we scale by the total market capitalization of the firms in our sample in year t. In the model, the level of the stock market is a constant multiple of output, hence these two indices coincide. In the data, the correlation between the two indices is 0.89 in levels and 0.75 in first differences.

We plot the two innovation indices in panels (a) and (b) of Figure 4. We see that both indices line up well with the three major waves of technological innovation in the U.S. First, both indices suggest high values of technological innovation in the 1930s, consistent with the evidence compiled in Field (2003), and Alexopoulos and Cohen (2009, 2011).[25] When we dissect the composition of the index we find that firms that primarily contribute to technological developments during the thirties are in the automobiles (such as General Motors) and telecommunication (such as AT&T) sectors. This description is consistent with studies that have examined which sectors and firms led to technological developments and progress in the 1930s (Smiley, 1994). Second, our measure suggests higher innovative activity during 1960s and early 1970s – a period commonly recognized as a period of high innovation in the U.S (see, e.g. Laitner and Stolyarov, 2003). Indeed, this was a period that saw development in chemicals, oil and computing/electronics – the same sectors we find to be contributing the most to our measure with major innovators being firms such as IBM, GE, 3M, Exxon, Eastman Kodak, du Pont and Xerox. Third, developments in computing and telecommunication have brought about the latest wave of technological progress in the 1990s

[25] Notably, our series peaks slightly earlier in the 1930s than Alexopoulos and Cohen (2011). This seems reasonable since our measure is based on patents as opposed to commercialization dates that their measure captures.

and 2000s, which coincides with the high values of our measure. In particular, it is argued that this is a period when innovations in telecommunications and computer networking spawned a vast computer hardware and software industry and revolutionized the way many industries operate. We find that firms that are main contributors to our measure belong to these sectors with firms such as Sun Microsystems, Oracle, EMC, Dell, Intel, IBM, AT&T, Cisco, Microsoft and Apple being the leaders of the pack.

For comparison, we also plot the number of patents per capita in panel (c). We see that our indices display different behavior than the total number of patents, especially in the beginning and towards the end of the sample.[26] In particular, post-1980, there is a rapid acceleration to the number of patents granted. Even though a fraction of this increase likely reflects an acceleration in the pace of technological innovation, an increase in patent grants can also arise due to changes in the legal environment (Henry and Turner, 2006).

To isolate the fluctuations in our index that are independent from changes in the number of patents granted, in panel (d) we plot the average value per patent – that is, we plot the numerator of (18) scaled by the total number of patents granted to firms in our sample in each year. Comparing panel (d) to panels (a) and (b), we can immediately see that most of the low-frequency fluctuation in our indices is driven by fluctuations in the average value of patents.[27]

Further, our economy-wide innovation measure allows us to shed some light to the puzzle raised by Kortum (1993), among others, regarding the secular increase in the ratio of R&D to patents. Indeed, as we see in panel (e), the ratio of R&D expenditures, deflated by the BEA R&D deflator, to the total number of patents granted in the US exhibits a secular increase. Kortum (1993) examines three of the potential explanations using a structural model, namely (i) a decline in the productivity in the research sector; (ii) an increase in the value of patents due to market expansion; and (iii) a decline in the patenting rate due to increased costs of patenting. Consistent with the conclusions in Kortum (1993), we find support for the second explanation. In particular, we construct a ratio of average value per patent at time t as the total estimated value of all granted patents in year t, granted to the set of firms in our sample, divided by the total number of patents granted to these firms in year t. As we see in panel (f), the ratio of costs to benefits – the difference between the series in panel (e) and the series in panel (d) – has shown a markedly slower decline.

Naturally, our time-series index comes with several caveats. First, part of the time-series fluctuation in our innovation index may be due to changes in the likelihood of patent approval – or more generally, the joint distribution of π_j and ξ_j. Along these lines, the degree of market efficiency may have changed over time. Last, the composition of patenting firms likely has

[26]The correlation between $\hat{\chi}_t$ and the log number of patents is equal to 60-75% in levels and 14-18% in first differences, depending on whether we scale $\hat{\chi}_t$ by output or aggregate stock market capitalization.

[27]In results that appear in an earlier version of this paper, we show that our index is also related to the index of Alexopoulos and Cohen (2009).

changed over the decades. Next we examine whether, despite all these caveats, our index contains meaningful information about economic growth.

Innovation and aggregate growth

Here, we examine the extent to which our economy-wide innovation measures account for short- and medium-run fluctuations in aggregate output growth and productivity. We measure output as the per capita gross domestic product deflated by the consumer price index, and productivity as the utilization-adjusted TFP from Basu et al. (2006). To study the relation between our innovation index and aggregate growth, we estimate the following specification

$$x_{t+\tau} - x_t = a_0 + a_\tau \, \log \hat{\chi}_t + \sum_{l=0}^{L} c_l \, x_{t-l} + u_{t+\tau}. \tag{19}$$

Here, x is our variable of interest – log aggregate output or log TFP – and χ is our index of innovation. We examine horizons of one to five years. We select the number of lags L using the BIC criterion, which advocates a lag length of one to three years depending on the specification. We compute standard errors using Newey-West with a maximum lag length equal to $\tau + 4$.

In the first row of Figure 5, we plot the response of aggregate output and total factor productivity to a unit standard deviation shock in our baseline innovation index (18). We see that, over a period of five years, a one-standard deviation increase in our index is followed by approximately a 6.5% increase in output growth and a 3.4% increase in aggregate productivity. The results using the alternative scaling – total market capitalization of firms in our sample as opposed to aggregate output – are comparable, though somewhat smaller in magnitude. As we see in the second row of Figure 5, the response of output and productivity to a unit standard deviation change in the alternative index scaled by market capitalization is 5.5% and 2.1% over five years, respectively.[28]

In sum, we find that waves of innovation are followed by an acceleration in aggregate output and productivity growth. These results are consistent with the estimates obtained from aggregating the coefficients from the firm-level analysis in Section 4.1. However, they are in contrast to Shea (1999) who finds only a weak relation between patents and measured TFP. Taken together, these findings suggest that our innovation index contains additional information about aggregate growth relative to what is included in simple patent counts. Further, the fact that the response of productivity and output are similar regardless of our choice of scaling variable – aggregate output or market capitalization – suggests that this predictability is not driven by information that is contained in the level of the stock market.

[28] In addition to (19), we also estimated impulse responses using bivariate VARs. The results are similar though the magnitudes are somewhat weaker: a one-standard deviation increase in our index is followed by approximately a 1.7-2.2% increase in output growth and a 0.6-1% increase in aggregate productivity. See Online Appendix Table A.3 for more details.

5 Conclusion

Using patent data for US firms from 1926 to 2010, we propose a new measure of the economic importance of each innovation that exploits the stock market response to news about patents. Our patent-level estimates of private economic value are strongly positively related to the scientific value of these patents – as measured by the number of forward citations that the patent receives in the future. Consistent with the predictions of Schumpeterian growth models, innovation using our measure is associated with substantial growth, reallocation and creative destruction. Our measure contains significant information in addition to citation-weighted patent counts; the relation between our measure and firm growth is substantially stronger. Aggregating our measure suggests that technological innovation accounts for significant medium-run fluctuations in aggregate economic growth and TFP.

In conclusion, three issues are worth reiterating. First, the main idea behind our innovation measure – that the private value of a patent can be extracted using stock price reaction around its grant – is quite general. Hence, we expect our measures of technological innovation and those constructed based on a similar idea around other events, such as drug approvals, to be useful beyond just the settings considered in the paper. Second, our empirical findings should be interpreted as providing support for the general Schumpeterian hypothesis that technological innovation is a significant driver of both economic growth and creative destruction. These predictions emerge in a wide variety of models that have been explored in the literature (e.g., (e.g. Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004)) and are not tied to the specific model used in the paper. Third, our innovation measure provides information that is complementary to the information contained in patent citations. By construction, our approach is geared towards measuring the private value of innovation; by contrast, patent citations are likely a better measure of the scientific value of the patent.

A A Model of Innovation

Here, we briefly present a simple model of innovation that is based on Atkeson and Burstein (2011).

Setup

There is a competitive representative firm producing a single consumption good (the numeraire) from a variety of intermediate goods according, to the production function

$$Y_t = \left[\int_0^{H_t} \theta_j^{1/\rho} \left(q_{j,t}\right)^{(\rho-1)/\rho} dj \right]^{\rho/(\rho-1)}. \tag{A.1}$$

The parameter $\rho > 1$ governs the elasticity of substitution between goods; θ_j indexes the quality of good j; and $q_{j,t}$ denotes the quantity of good j produced at time t. The non-decreasing process H_t represents the current measure of intermediate goods, which evolves according to

$$H_t = H_{t-1} + N_t,$$

where N is a positive random variable described below. Importantly, new goods created at time t draw their quality θ from a distribution $f_t(\theta)$ that is allowed to vary over time. Denote the mean of that distribution at time t by $\bar{\theta}_t = \int \theta f_t(\theta) d\theta$. To have a balanced growth path, we assume that $\bar{\theta}_t N_t = \chi_t X_{t-1}$, where

$$X_t \equiv \int_0^{H_t} \theta_j \, dj, \tag{A.2}$$

and $\chi_t > 0$ is an i.i.d. random variable. These assumptions imply that

$$X_t = X_{t-1} \, (1 + \chi_t) \tag{A.3}$$

Each good is produced according to a linear production technology,

$$q_{j,t} = l_{j,t}. \tag{A.4}$$

In the model, all goods are patented. The firm that owns the patent for good j acts like a monopolist.

Last, consumers have log utility over consumption,

$$U(C_t) = \log C_t, \tag{A.5}$$

and discount the future using a subjective discount factor β. Households inelastically supply a unit of labor services at the equilibrium wage w.

Equilibrium

Using standard arguments, it is straightforward to show that the inverse demand for good j is given by

$$p_{j,t} = \left[\frac{q_{j,t}}{Y_t}\right]^{-1/\rho} \theta_j^{1/\rho}. \tag{A.6}$$

Using (A.6), total profits from producing good j equal

$$\Pi_{j,t} \equiv p_{j,t} \, q_{j,t} - w_t \, q_{j,t} = q_{j,t}^{1-1/\rho} \, (Y_t \, \theta_j)^{1/\rho} - w_t \, q_{j,t}. \tag{A.7}$$

Maximizing the above expression with respect to quantity produced (q) yields

$$\begin{aligned} q_{j,t} &= Y_t \, \theta_j \left[\frac{w_t}{1 - 1/\rho}\right]^{-\rho} \\ &= \theta_j X_t^{-1}, \end{aligned} \tag{A.8}$$

where the last equality follows from clearing the labor market – requiring that

$$\int_0^{H_t} q_{j,t}\, dj = 1. \tag{A.9}$$

Using (A.1), we get that aggregate output – and consumption – are given by

$$Y_t = X_t^{1/(\rho-1)}, \tag{A.10}$$

while the equilibrium wage is given by

$$w_t = \frac{\rho - 1}{\rho}\, Y_t, \tag{A.11}$$

while flow profits from owning a patent to good j are

$$\Pi_{j,t} = \frac{1}{\rho}\, \theta_j\, Y_t^{2-\rho}. \tag{A.12}$$

Next, we examine the market value of a patent. The market value of a patent for good j is equal to the present value of the monopoly profits associated with good j, using the household's stochastic discount factor,

$$\xi_{j,t} \equiv E_t \left[\sum_{s=t}^{\infty} \beta^{s-t} \frac{U'(C_s)}{U'(C_t)}\, \Pi_{j,s} \right] = \theta_j\, Y_t\, X_t^{-1}\, B \tag{A.13}$$

where

$$B = \frac{1}{\rho}\, E_t \left[\sum_{s=t}^{\infty} \beta^{s-t} \left(\frac{X_t}{X_s} \right) \right]. \tag{A.14}$$

is a constant.

Using (A.13), we add up the value of all new patents at time t, and divide by output,

$$\begin{aligned} \hat{\chi}_t = Y_t^{-1} \int_{H_{t-1}}^{H_t} \xi_{j,t}\, dj &= B\, X_t^{-1} \int_{H_{t-1}}^{H_t} \theta_j\, dj \\ &\propto \frac{X_t - X_{t-1}}{X_t} \\ &= \frac{\chi_t}{1 + \chi_t}. \end{aligned} \tag{A.15}$$

The key result of the model is that, to a first-order approximation (small χ_t), the aggregate index $\hat{\chi}_t$ is proportional to the growth rate in aggregate output and productivity χ_t.

Last, rather than dividing by aggregate output, we could also have divided by the value of the stock market, which is equal to

$$M_t = E_t \left[\sum_{s=t}^{\infty} \beta^{s-t} \frac{U'(C_s)}{U'(C_t)}\, (Y_s - w_s) \right] = \frac{1}{\rho\,(1-\beta)}\, Y_t. \tag{A.16}$$

Since the stock market is proportional to aggregate output, similar results obtain.

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Tables and Figures

Table 1: Estimates of Patent Value: Descriptive Statistics

Moment	C	$C/\bar{C}$	R_f (%)	$E[v\|R_f]$ (%)	ξ
Mean	10.26	1.18	0.07	0.32	10.36
Std. Dev.	20.13	1.98	3.92	0.20	32.04
Percentiles					
p1	0	0	-9.93	0.11	0.01
p5	0	0	-5.15	0.14	0.04
p10	0	0	-3.55	0.16	0.11
p25	1	0.20	-1.67	0.20	0.73
p50	5	0.62	-0.09	0.27	3.22
p75	11	1.38	1.62	0.37	9.09
p90	24	2.78	3.82	0.53	22.09
p95	38	4.06	5.73	0.68	38.20
p99	90	8.84	11.49	1.07	121.39

The table reports the distribution of the following variables across the patents in our sample: the number of future citations till the end of our sample period C; the number of citations scaled by the mean number of cites to patents issued in the same year $\bar{C}$; the market-adjusted firm returns R_f on the 3-day window following the patent issue date; the filtered component of returns $E[v|R_f]$ related to the value of innovation – using equation (4); and the filtered dollar value of innovation ξ using equation (3) deflated to 1982 (million) dollars using the CPI. Patents are always issued on Tuesdays, hence the 3-day return is computed as the cumulative market adjusted return between Tuesday and Thursday. Market adjusted returns are computed as the difference between the firm return (CRSP holding period return) minus the return of the CRSP value-weighted index. We restrict attention to the patents for which we have non-missing data on three day announcement return, market capitalization and return volatilities – inputs needed to compute our $\hat{\Theta}$ measure. The sample contains 1,801,879 patents.

Table 2: Forward Citations and Patent Market Values

	(1)	(2)	(3)	(4)	(5)
$\log(1 + C_j)$	0.174	0.099	0.054	0.013	0.004
	(9.99)	(9.43)	(10.28)	(14.05)	(5.23)
N	1,801,301	1,801,301	1,801,301	1,801,301	1,801,301
R^2	0.205	0.707	0.790	0.925	0.952
Controls					
Firm Size	-	Y	Y	Y	Y
Volatility	-	-	Y	Y	-
Fixed Effects	CxT	CxT	CxT	CxT	CxT
				F	FxT

Table presents the results from estimating equation (7) relating the estimated patent value to the forward citations to the patent. The dollar value of a patent is constructed using equation (3). For details on our baseline empirical procedure see Section 1.4. We include grant-year fixed effects throughout. Depending on the specification we also include: USPTO 3-digit technology classification classes interacted with grant year fixed effects, CxT; our estimate of the firm's idiosyncratic volatility; firm size, measured as market capitalization on the day prior to the patent issue date; firm fixed effects, F; firm interacted with grant year fixed effects, FxT. We cluster the standard errors by the patent grant year, and report t-statistics in parenthesis. The sample contains 1,801,301 (out of 1,801,879) patents for which we have information on technology class. All variables are winsorized at the 1% level using annual breakpoints.

Table 3: Descriptive Statistics: Firm Innovation and Growth

	Mean	SD	p10	p25	p50	p75	p90
Innovation Output, SM-weighted (θ_f^{sm}, %)	3.1	12.1	0.0	0.0	0.0	0.6	7.1
Innovation Output, C-weighted (θ_f^{cw}, %)	3.8	12.8	0.0	0.0	0.0	0.6	9.4
Profits, growth rate (%)	5.9	42.5	-28.9	-7.6	5.4	19.4	41.5
Output, growth rate (%)	5.0	38.8	-24.9	-6.8	4.7	16.8	35.5
Capital stock, growth rate (%)	9.9	34.8	-9.0	-0.2	6.6	17.3	36.4
Employment, growth rate (%)	3.9	35.0	-20.5	-5.6	2.5	13.4	30.8
TFPR, log (%)	-31.8	40.3	-75.2	-49.9	-30.2	-11.2	11.8

The Table presents descriptive statistics for the firm's innovative output (θ_f, defined in equation (10)) which weigh patents using their stock-market reaction (SM, see equation (8)) and citations (CW, see equation (9)). In addition, we report the growth rate in firm gross profits (COMPUSTAT: sale minus COMPUSTAT: cogs, deflated by the CPI); firm output (COMPUSTAT: sale plus change in inventories COMPUSTAT: invt, deflated by the CPI); firm capital stock (COMPUTAT: ppegt, deflated by the NIPA price of equipment); firm employment (COMPUSTAT: emp); and firm TFPR, constructed using the methodology of Olley and Pakes (1996) applied on Compustat data using the procedure in Imrohoroglu and Tuzel (2013). All variables are winsorized at the 1% level using annual breakpoints.

Table 4: Innovation and Firm Growth

a. Profits									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.018	0.029	0.036	0.042	0.046	-0.016	-0.030	-0.032	-0.035	-0.038
[3.54]	[4.43]	[3.69]	[3.76]	[3.55]	[-3.00]	[-5.09]	[-7.28]	[-6.01]	[-5.85]

b. Output									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.009	0.015	0.021	0.026	0.032	-0.015	-0.032	-0.041	-0.046	-0.051
[3.10]	[3.39]	[3.15]	[2.91]	[3.39]	[-3.58]	[-7.47]	[-8.97]	[-8.23]	[-7.81]

c. Capital									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.010	0.020	0.028	0.033	0.038	0.000	-0.009	-0.019	-0.028	-0.038
[8.24]	[6.89]	[6.07]	[4.66]	[4.33]	[-0.07]	[-1.63]	[-2.53]	[-3.37]	[-4.45]

d. Labor									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.007	0.013	0.019	0.023	0.025	-0.008	-0.019	-0.024	-0.026	-0.027
[5.28]	[4.51]	[4.24]	[3.86]	[3.38]	[-2.00]	[-4.81]	[-5.32]	[-4.96]	[-4.56]

e. TFPR									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.013	0.017	0.019	0.023	0.024	-0.002	-0.006	-0.010	-0.015	-0.017
[2.34]	[2.29]	[2.78]	[3.50]	[4.31]	[-1.23]	[-2.64]	[-3.55]	[-4.77]	[-4.35]

Table reports point estimates of equation (12) for firm profits, output, capital, employment and TFPR. See notes to Table 3 for variable definitions. We relate firm growth and productivity to innovation by the firm (θ_f^{SM}, defined in equation (10); see also (8)) and the innovation by the firm's competitors ($\theta_{I\setminus f}^{SM}$, the average innovation of other firms in the same SIC3 industry, see equation (11)). Controls include one lag of the dependent variable, log values of firm capital, employment, and the firm's idiosyncratic volatility, and industry (I) and time (T) fixed effects. All variables are winsorized at the 1% level using annual breakpoints. Standard errors are clustered by firm and year. All right-hand side variables are scaled to unit standard deviation.

Table 5: Innovation and Firm Growth (using citation-weighted patents)

	Firm					Competitors				
	1	2	3	4	5	1	2	3	4	5
a. Profits										
	0.006	0.011	0.016	0.020	0.025	-0.003	-0.003	-0.002	0.001	0.001
	[5.00]	[5.97]	[5.58]	[5.59]	[5.81]	[-1.82]	[-1.30]	[-1.18]	[-0.38]	[-0.36]
b. Output										
	0.002	0.005	0.011	0.015	0.019	0.001	0.002	0.002	0.002	0.002
	[1.36]	[2.00]	[3.58]	[3.88]	[4.42]	[0.16]	[0.36]	[0.17]	[0.14]	[0.15]
c. Capital										
	-0.003	0.000	0.004	0.010	0.015	0.002	0.003	0.003	0.003	0.004
	[-2.46]	[-0.06]	[1.63]	[3.04]	[3.51]	[1.63]	[1.18]	[0.89]	[0.63]	[0.79]
d. Labor										
	-0.001	0.002	0.007	0.012	0.015	0.005	0.007	0.009	0.011	0.013
	[-0.92]	[0.92]	[2.74]	[3.73]	[3.82]	[2.82]	[2.58]	[2.79]	[2.56]	[2.54]
e. TFPR										
	0.005	0.008	0.008	0.009	0.010	-0.001	-0.001	0.001	0.002	0.003
	[3.66]	[4.22]	[4.08]	[3.97]	[4.00]	[-0.83]	[-0.39]	[0.22]	[0.76]	[0.98]

Table reports point estimates of equation (12) for firm profits, output, capital, employment and TFPR. See notes to Table 3 for variable definitions. We relate firm growth and productivity to innovation by the firm (weighted using citations, θ_f^{CW}, defined in equation (10); see also (9)) and the innovation by the firm's competitors ($\theta_{I\setminus f}^{CW}$, the average innovation of other firms in the same SIC3 industry, see equation (11)). Controls include one lag of the dependent variable, log values of firm capital, employment, and the firm's idiosyncratic volatility, and industry (I) and time (T) fixed effects. All variables are winsorized at the 1% level using annual breakpoints. Standard errors are clustered by firm and year. All right-hand side variables are scaled to unit standard deviation.

Table 6: Innovation and Firm Growth (both measures)

a. Profits

	Firm					Competitors				
	1	2	3	4	5	1	2	3	4	5
SM	0.017	0.027	0.033	0.038	0.041	-0.015	-0.029	-0.031	-0.034	-0.036
	[3.29]	[4.11]	[3.41]	[3.53]	[3.36]	[-2.98]	[-5.04]	[-7.05]	[-5.74]	[-5.54]
CW	0.002	0.006	0.010	0.014	0.019	-0.002	-0.001	0.000	0.003	0.003
	[1.02]	[1.97]	[2.25]	[2.73]	[3.27]	[-0.92]	[-0.29]	[-0.10]	[0.57]	[0.45]

b. Output

	Firm					Competitors				
	1	2	3	4	5	1	2	3	4	5
SM	0.009	0.015	0.019	0.023	0.028	-0.015	-0.032	-0.041	-0.045	-0.051
	[2.94]	[3.14]	[2.91]	[2.71]	[3.20]	[-3.70]	[-7.73]	[-8.87]	[-8.00]	[-7.53]
CW	-0.001	0.000	0.005	0.008	0.012	0.002	0.004	0.004	0.004	0.005
	[-0.52]	[-0.09]	[1.45]	[1.92]	[2.45]	[0.79]	[1.19]	[1.08]	[0.99]	[0.94]

c. Capital

	Firm					Competitors				
	1	2	3	4	5	1	2	3	4	5
SM	0.013	0.023	0.029	0.033	0.038	-0.001	-0.010	-0.019	-0.028	-0.038
	[9.07]	[6.61]	[5.91]	[4.58]	[4.27]	[-0.22]	[-1.75]	[-2.61]	[-3.40]	[-4.44]
CW	-0.007	-0.008	-0.005	0.000	0.003	0.003	0.005	0.006	0.006	0.008
	[-4.84]	[-3.56]	[-1.90]	[-0.02]	[0.68]	[2.47]	[2.17]	[1.87]	[1.54]	[1.67]

d. Labor

	Firm					Competitors				
	1	2	3	4	5	1	2	3	4	5
SM	0.008	0.014	0.018	0.022	0.023	-0.009	-0.020	-0.024	-0.026	-0.027
	[6.42]	[4.40]	[4.05]	[3.69]	[3.24]	[-0.22]	[-1.75]	[-2.61]	[-3.40]	[-4.44]
CW	-0.004	-0.003	0.001	0.005	0.008	0.006	0.009	0.012	0.014	0.016
	[-2.68]	[-1.26]	[0.48]	[1.39]	[1.76]	[3.35]	[3.32]	[3.51]	[3.18]	[3.06]

e. TFPR

	Firm					Competitors				
	1	2	3	4	5	1	2	3	4	5
SM	0.013	0.016	0.019	0.022	0.023	-0.002	-0.006	-0.010	-0.015	-0.017
	[2.21]	[2.16]	[2.66]	[3.35]	[4.14]	[-1.17]	[-2.51]	[-3.50]	[-4.69]	[-4.31]
CW	0.001	0.003	0.002	0.002	0.002	0.000	0.001	0.003	0.004	0.005
	[0.98]	[1.87]	[1.17]	[0.99]	[0.94]	[0.37]	[0.49]	[1.08]	[1.79]	[1.98]

Table relates firm growth and productivity to innovative output – equation (12) in the paper – using both the stock-market (SM) and the citation-weighted measure (CW). See notes to Tables 3, 4, and 5 for variable definitions and more details on the specification. All right-hand side variables are scaled to unit standard deviation.

Figure 1: Share turnover during patent issuance weeks

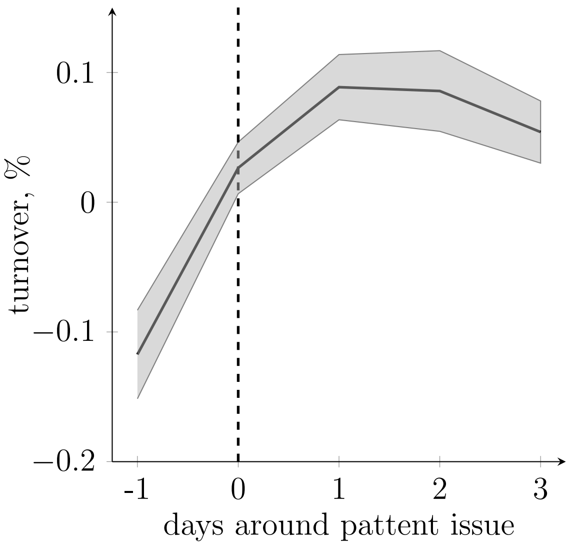


Figure plots the share turnover around patent issuance days. Share turnover h is the ratio of daily volume (CRSP: vol) to shares outstanding (CRSP: shrout). The median daily share turnover is 1.29%. We report the coefficient estimates b_l, $l = -1 \ldots 3$, (and 90% confidence intervals) from the following specification:

$$h_{fd} = a_0 + \sum_l b_l \, I_{fd+l} + c \, Z_{fd} + \varepsilon_{fd},$$

where the indicator variable I takes the value one if firm f is issued a patent on day d; the vector of controls Z_{fd} includes firm-year and calendar day fixed effects. Standard errors are clustered by year.

Figure 2: Forward citations and patent market value

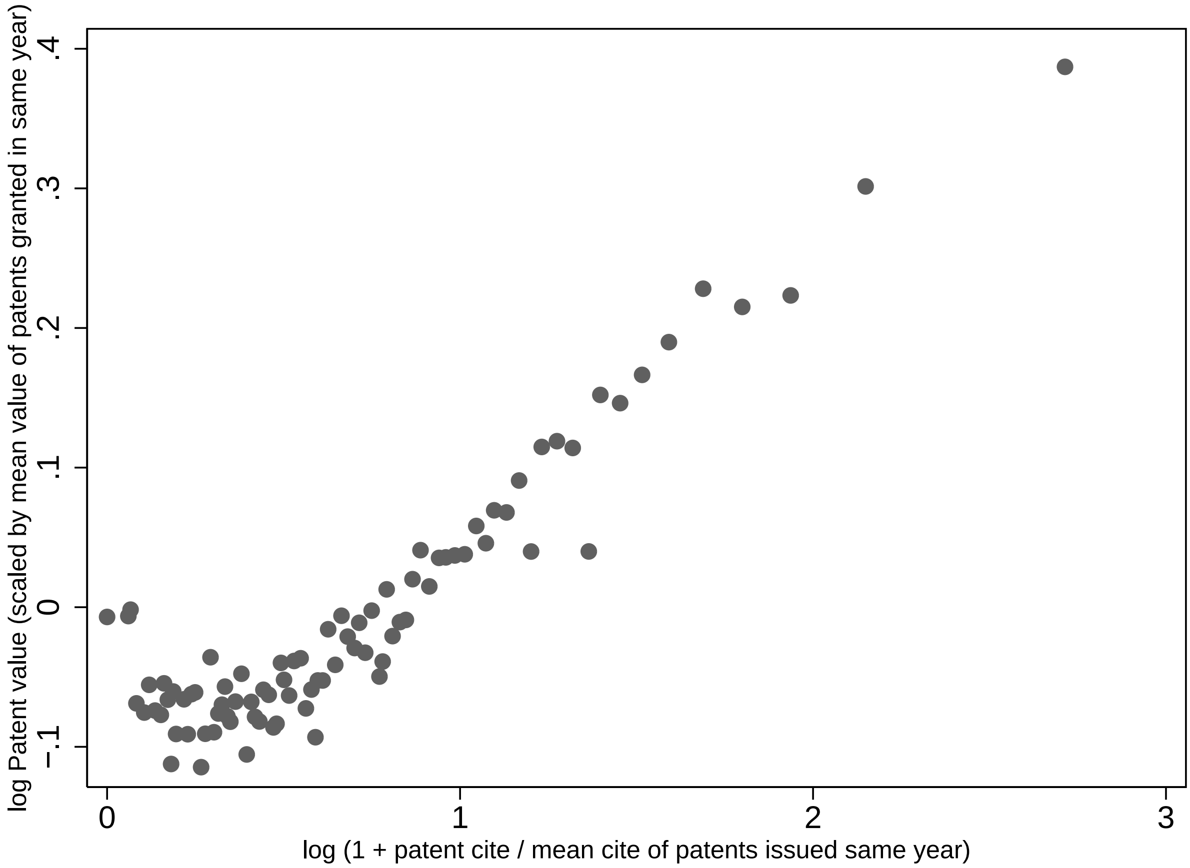


Figure plots the cross-sectional relation between forward patent citations and the estimated market value of patents. We group the patent data into 100 quantiles based on their cohort adjusted citations $(1 + C/\bar{C})$. The horizontal axis plots the log of average cohort adjusted patent citations in each quantile. The vertical axis plots the logarithm of the average patent value in each quantile (scaled by the average value of patents granted in the same year). Patent values are constructed according to equation (3) in the main text.

Figure 3: Relation between stock market reaction and number of citations across placebo experiments

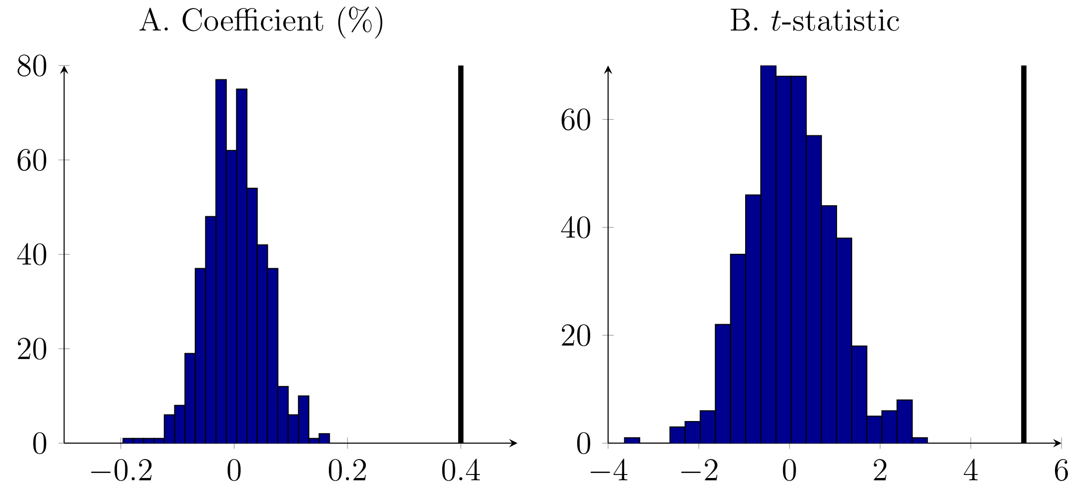
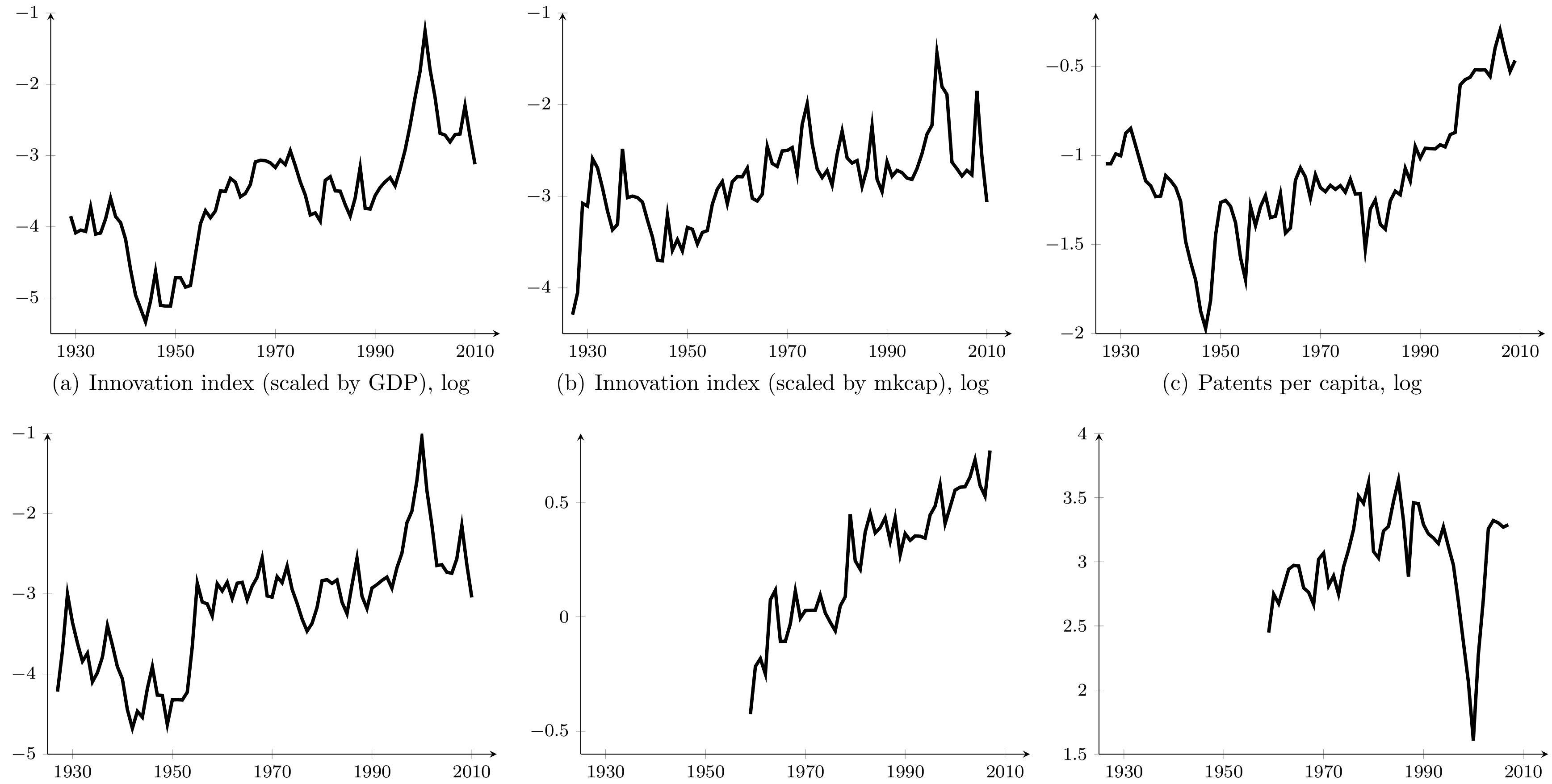


Figure plots distribution of estimated coefficients $\hat{b}$ (panel A) and t-statistics (panel B), from estimating equation (7) – corresponding to the specification of column (5) in Table 2 – across 500 placebo experiments. In each placebo experiment, we randomly generate a different issue date for each patent within the same year the patent is granted to the firm. We then reconstruct our measure using these placebo grant dates. The solid line on the right corresponds to the estimated coefficient (and t statistic) using the real data – column (5) in Table 2.

Figure 4: Aggregate Measures of Innovation



(a) Innovation index (scaled by GDP), log

(b) Innovation index (scaled by mkcap), log

(c) Patents per capita, log

(d) Value/ Patent, log

(e) R&D Expenditure / Patent, log

(f) Costs vs Benefits of RD, log

Panel A plots the log values of the baseline innovation index – see equation (18) in the text – which is equal to the sum of the market reaction of patents granted in year t scaled by aggregate output. Panel B presents the alternative index constructed by scaling the market value of patents by the market capitalization of all the firms at the end of the year t. Panel C plots the total number of patents granted each year divided by population from the U.S. Census Bureau. Panel D plots the mean market value per patented granted each year (in logs). Panel E plots the real value of R&D expenditure (using the BEA deflator for R&D) to the total number of patents granted, in logs. Panel F plots the difference between the series in Panels D and E.

Figure 5: Innovation and Aggregate Growth

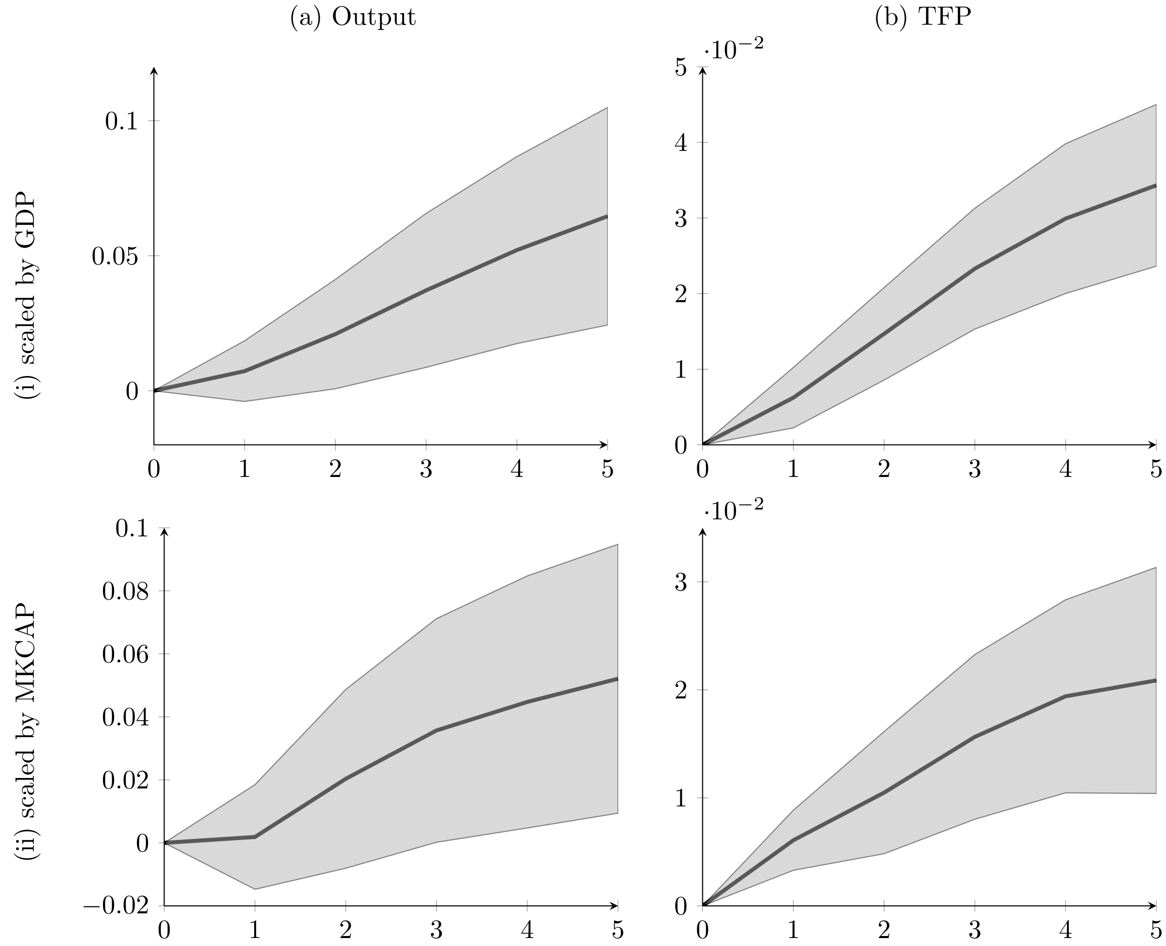


Figure shows the estimated response of output per capita and productivity to innovation using equation (19) in the main text. Dotted lines represent 90% confidence intervals using Newey-West standard errors with maximum lag length equal to two plus the horizon. Productivity is utilization-adjusted TFP from Basu et al. (2006). Output is gross domestic product (NIPA Table 1.1.5) divided by the consumption price index (St Louis Fed, CPIAUCNS). Output per capita is computed using population from the U.S. Census Bureau.

Online Appendix to "Technological Innovation, Resource Allocation and Growth"

Leonid Kogan, Dimitris Papanikolaou,
Amit Seru and Noah Stoffman

A Patent Data

Our measure of innovation relies on using information on patents that a firm creates and the stock market response to news about these patents. We now discuss the data that we employ in our analysis.

Patents in the United States are granted by the United States Patent and Trademark Office (USPTO). We download the entire history of U.S. patent documents from Google Patents.[1] Each of about 7.8 million patent files was downloaded using an automation script.[2]

To construct our measure of innovation, we match all patents in the Google data to corporations whose returns are in the CRSP database. Patent regulations require that only an individual, not a corporation, can be an inventor. However, the inventor can assign the granted property rights to a corporation or another person. Therefore, when patents are granted they always have an inventor, and sometimes an "assignee", that is, one or more corporations or persons.

For most patents, Google provides a text version of the patent document, created using OCR software. We use this text version of the document to extract the names of corporations to which patents are assigned. However, OCR technology is imperfect, and many of the downloaded documents include a great deal of garbled text. We therefore make use of a number of text analysis algorithms to extract relevant information from the documents.

Our sample covers patents granted between 1926 and 2010 matched to firms with returns in CRSP database. Since we merge our patent data with data on stock returns, we are limited to the period after 1926, when the CRSP database begins.

[1] `http://www.google.com/patents`

[2] Google also makes available for downloading bulk patent data files from the USPTO. The bulk data does not have all of the additional "meta" information including classification codes and citation information that Google includes in the individual patent files. Moreover, the quality of the text generated from Optical Character Recognition (OCR) procedures implemented by Google is better in the individual files than in the bulk files provided by the USPTO. As explained below, this is crucial for identifying patent assignees.

Matching patents to firms

Here, we briefly discuss the steps our matching procedure followed, and provide extensive details Section B. We search the document for the words "assignee" or "assigned" and extract the text that immediately follows. This text is either a company name, or the name of an individual to whom the patent is assigned. We then count the number of times each assignee name appears across all patent documents. We compare each assignee name to more common names, and if a given name is "close", in the sense of the Levenshtein distance, to a much more common name, we substitute the common name for the uncommon name.[3] For example, one of the most common names is "General Electric Company", which is associated with over 43,000 patents. We substitute this name for the far less common, but quite similar, names "General Electbic Oohpany", "General Electbic Cqhpany", and "Genebal Electbic Compakt".

At this point, we have an assignee name for each patent. These names must be matched to a company identifier such as the CRSP permco. This is accomplished in two steps. We begin by looking only at patents that are also in the NBER database. For each assignee name identified in the steps above, we count how many different permcos are matched to patents in the NBER database. For example, all of the patents with an assignee name "General Electric Company" are matched to one permco in the NBER database. We can therefore safely assume that *all* of the patents assigned to the General Electric Company can be matched to that permco, *even for patents not included in the NBER data*. Remaining assignee names are matched to CRSP firm names using a name matching algorithm.[4] The algorithm uses a score based on the inverse word frequency to match assignee names to possible company names. For example, the word "American" is quite common in company names, and so contributes little to name matching; the word "Bausch" is quite uncommon, so it is given much more weight. Visual inspection of the matched names confirms very few mistakes in the matching.

Extracting patent citations

We extract patent citations from three sources. First, all citations for patents granted between 1976 and 2011 are contained in text files available for bulk downloading from Google. These citations are simple to extract and likely to be free of errors, as they are official USPTO data. Second, for patents granted before 1976, we extract citations from the OCR text generated from the patent files. We search the text of each patent for any 6- or 7-digit numbers, which could be patent numbers. We then check if these potential patent numbers are followed closely by the corresponding grant date for that patent; if the correct date appears, then we can be certain that we have identified a patent citation. Since we require the date to appear near any potential patent number, it is unlikely that we would incorrectly record a patent citation – it is far more likely that we would fail

[3] The Levenshtein distance is the number of edits required to make one string match another string, where an edit is inserting, deleting, or substituting one character.

[4] The algorithm is based on code written by Jim Bessen, available at `http://goo.gl/m4AdZ`.

to record a citation than record one that isn't there. Third, we complement our citation data with the hand-collected reference data of Nicholas (2008). See Section B of this Appendix for a detailed explanation of this process.

Summary statistics

We now provide some statistics that lend credence to our method for extracting patent information. Table A.1 shows the number of patents we match to companies. Of the 6.2 million patents granted in or after 1926, we find the presence of an assignee in 4.4 million. The matching procedure provides us with a database of 1.9 million matched patents, of which 523,301 (27%) are not included in the NBER data. Figure A.1 graphs the total number of patents matched by the year the patent was granted. Patents included in the NBER data, which is the most comprehensive database previously available, are shown in light shading. Patents unique to our database are presented in dark shading. Note that the two sets of data appear to fit together fairly smoothly, and that even during the period covered by the NBER data, our database adds an average of 2,187 patents to the NBER data.[5]

Table A.2 provides additional summary statistics. Overall, our data provides a matched permco for 66% of all patents with an assignee, or 31% of all granted patents. By comparison, the NBER patent project provides a match for 32% of all patents from 1976–2006, so our matching technique works quite well, even using only data extracted from OCR documents for the period before the NBER data. Another point of comparison is Nicholas (2008), who uses hand-collected patent data covering 1910 to 1939. From 1926–1929, he matches 9,707 patents, while our database includes 8,858 patents; from 1930–1939 he has 32,778 patents while our database includes 47,036 matches during this period.

[5]We use information on the patent-assignee match in the NBER data to assist with our matching, so the match during the overlapping period is mostly the same, by construction. An exception is for cases where there is apparently a mistake in the NBER match and our patent-assignee frequency-based matching system corrects an error.

B Patent Data Construction – Details

In this section we explain in detail how we constructed our new patent data set. The raw data are very large and not very well structured, and thus required a great deal of effort to clean. We used a number of techniques to extract, clean, and match assignees from patents. As with any such project there is a trade-off between type-I and type-II errors (in this case, failing to match an assignee to CRSP or incorrectly matching an assignee to CRSP). Our approach was to be as conservative as possible, attempting to minimize mismatches while at the same time extracting as many correct matches as possible.

B.1 Data sources

We use three sources of data to construct the new patent database:

1. Details of patents granted from 1976–2010 is available in high-quality text files available for bulk downloading from Google, through a special data-hosting arrangement with the United States Patent and Trademark Office (USPTO). The text files use one of two data structures that allows relatively straightforward data extraction: files for 2001–present use XML, while files for 1976–2000 use a fixed-width data structure with labeled fields.
2. Patents granted prior to 1976 are also stored on Google, but only in individual web pages (one per patent). Information during this period is drawn from Optical Character Recognition (OCR) of original patent documents, and is of highly-variable quality. There is very limited, if any, structure to these files.
3. We use the NBER patent data (Hall and Trajtenberg, 2001), which covers the period 1976–2006, to help with the matching and to validate our other data extraction methods.

Due to varying data sources and quality over time, it worth stressing that from 1976–2010 we use the *official records* of the USPTO. As we discuss below, we are able to provide some additions and corrections to the NBER data during the period of overlap with our data. Prior to 1976 the data are more difficult to work with, but we have implemented a number of sophisticated text analysis algorithms to create a very high-quality database.

Downloading individual patent files

We downloaded individual patent data from Google. The URL for each patent's summary page is of the form `http://www.google.com/patents/?id=RD0yAAAAEBAJ`, where `RD0y` is a 4-character code used by Google to identify each patent. The IDs use any of the characters $\{a, \ldots, z, A, \ldots, Z, 0, \ldots, 9, \_, -\}$. There are $64^4 = 16.8$ million possible IDs, but only about 8 million patents. However, all 16.8 million URLs must be checked, because there is no publicly-available mapping of patent numbers to the Google ID.

A screen shot of the summary page for the patent with id RD0y, which is patent 4,345,262, is shown in Figure 1. The main page includes—when available—the title of the patent, the filing and grant dates, the abstract, inventor(s), original assignee(s), current classifications, and a record of citations (out-cites) and references (in-cites). The information reported on this page by Google was gleaned from the OCR analysis of the original patent document, and consequently less information is reported for older documents, especially patents granted before 1976.

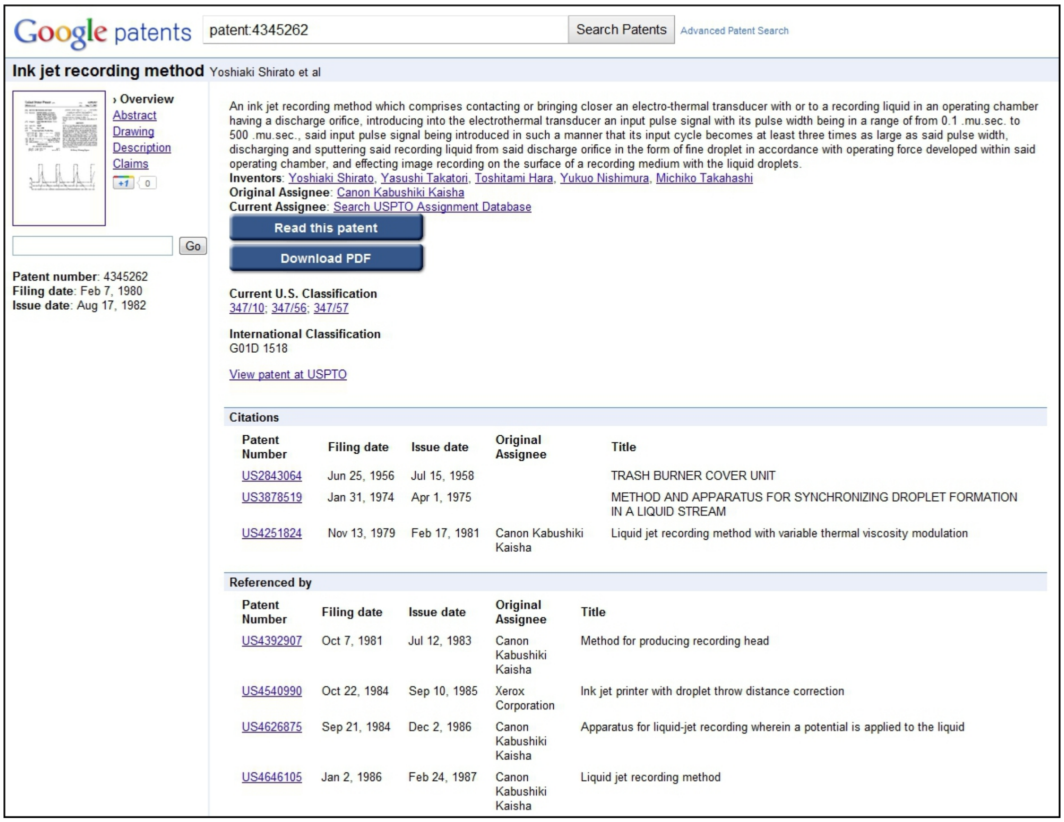


Figure 1: Google summary page for U.S. patent 4,345,262

Using a Perl automation script, we sequentially navigated to each of the 16.8 million patent summary pages.[6] From this page, we stored all available information. The script then loaded the "Read this patent" link, which loads a PDF version of the patent document. From here, we loaded the "plain text" version of the document, which is simply the text derived from OCR of the PDF document. Examples of these pages are shown in Figures 2 and 3. We saved the complete text of the plain text version of each patent. After compression, the complete archive of text requires approximately 56 gigabytes of disk space.

[6]Google generally blocks users from downloading so many web pages. We are grateful to Hal Varian for his assistance with arranging permission to access these pages.

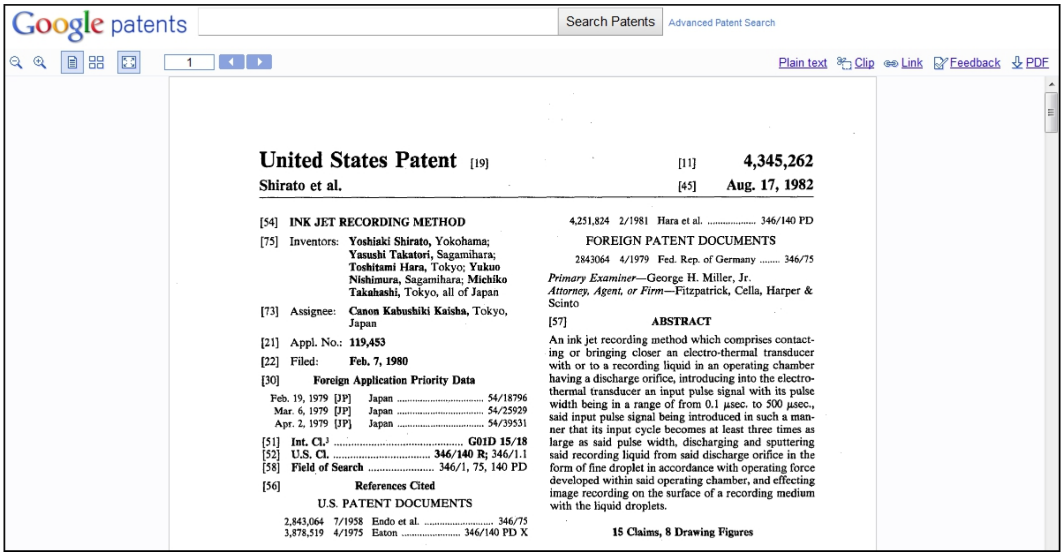


Figure 2: PDF view

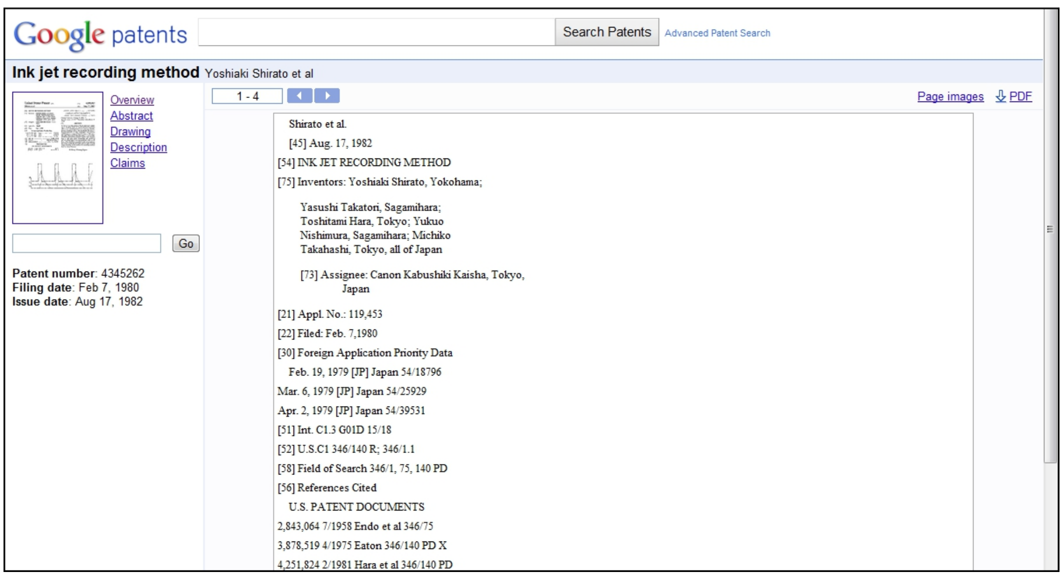


Figure 3: Plain text view

Download bulk patent files

As part of a special arrangement with the USPTO, Google also makes available for downloading bulk patent data files. The bulk data does not have all of the additional "meta" information including classification codes and citation information that Google includes in the individual patent files. Moreover, the quality of the text generated from OCR procedures implemented by Google is better in the individual files than in the bulk files provided by the USPTO. We therefore do not use the bulk download files for data in the pre-NBER period.

For the post-NBER period, however, the bulk data files are of extremely high quality because they are based on digital patent records as opposed to OCR data drawn from images of patent documents. These data files are provided either in XML format or in a fixed-width record format. In both cases, all fields (inventor name, grant date, etc.) are clearly identified. We rely on these files to construct the database during the post-NBER period (2006–2009) and to make additions and corrections to the NBER data.

B.2 Identifying assignees

Extracting assignee names

For data during the post-1976 period, we can use the XML files available for bulk download to identify the assignee with virtually no errors.

During the pre-1976 period, we cannot rely solely on Google's extraction of the filing and grant dates or the assignee name because the OCR for patents frequently has errors. As an example, consider patent 1,131,249, shown in Figure 4.


UNITED STATES PATENT OFFICE.

EARLE R. KNIGHT, OF NORWOOD, OHIO, ASSIGNOR, BY MESNE ASSIGNMENTS, TO ALLIS-CHALMERS MANUFACTURING COMPANY, A CORPORATION OF DELAWARE.

RETAINING-RING FOR DYNAMO-ELECTRIC MACHINES.

1,131,249. Specification of Letters Patent. Patented Mar. 9, 1915.

Application filed May 1, 1909. Serial No. 493,399.

To all whom it may concern:

Be it known that I, Earle R. Knight, a citizen of the United States, residing at Norwood, in the county of Hamilton and State of Ohio, have invented certain new and useful Improvements in Retaining-Rings for

ring is shown in perspective in Fig. 3. It comprises two segmental duplicate interchangeable parts each part of which has two male portions 16 and two female portions 17. The male and female portions of one part of the split retaining rings are respectively

Figure 4: Title page of patent 1,131,249

It is clear to a human reader that this patent was assigned to the Allis-Chalmers Manufacturing Company, but the OCR for this patent reads

```
EASLS B. KNIGHT, OF NORWOOD, OHIO, ASSIGNOR,, BY MESH'S ASSIGN1IBNTS, TO ALUSCHALME&S
MANOTAC/rURING- COMPANY, A COBPOBAT'1OH OF DELAY/ABE.
```

Consequently, Google records the assignee as "BY MESH S ASSIGNIIBNTS", which is clearly not accurate.

We therefore rely on a number of textual analysis algorithms to extract the assignee name from the full text files we saved for each patent. In general, our approach to performing a "fuzzy" match on a text string is to use the maximum likelihood n-gram approach described by Norvig (2009).

We begin by identifying the text where the assignee, if there is one, will be named. We do this by searching for words that appear similar to “assign”, “assignor”, or “assignee”. When found near the beginning of the patent document, this word is typically followed closely by the name of the assignee, so we extract a text string of 200 characters for further processing. The assignee may be a person, or a corporation, in which case the name will include a word like “company”, “corporation” or “incorporated”. If the word “assign” and its variants are not found, we assume the inventor did not assign the patent to another entity.

Cleaning assignee names

After extracting the string that is likely to contain the assignee name, additional cleaning is necessary. Because of OCR errors, company names may be garbled. For example, the General Electric Company, which has more than 43,000 patents in our data, appears as “General Electbic Oohpany”, “General Electbic Cqhpany”, and “Genebal Electbic Compakt”, among hundreds of other misspellings. To fix these, we first count how many patents have been granted to each assignee name, regardless of how the assignee name is spelled. In this example, General Electric Company appears in 42,693 patents, while each of the misspelled variants appears fewer than 5 times.

We then calculate the Levenshtein edit distance[7] between each assignee name and all other names that have more patents. If any assignee name is close to another assignee name that is associated with many more patents, then the more common assignee name is substituted for the less common name. This algorithm correctly identifies all of the misspellings noted above as being General Electric.

After cleaning assignee names, we manually checked which misspelled names were matched to the 500 assignees with the most patents to confirm that no significant errors were introduced in this step.

Matching to CRSP

Having extract a list of assignee names, the next step is to match company names to the CRSP permco identifier. This is accomplished in three steps.

We begin by looking only at those patents that are included in the NBER patent database.

[7]The Levenshtein distance is the number of edits required to transform one string into another string, where allowed edits are inserting, deleting, or substituting one character. For example, the Levenshtein distance between “patent” and “parent” is 1, while the distance between “patent” and “apparent” is 3.

For each assignee name identified in the steps above, we count how many *different* permcos are matched to patents in the NBER database. For example, all of the patents with an assignee name "General Electric Company" are matched to one permco in the NBER database. We can therefore safely assume that *all* of the patents assigned to the General Electric Company can be matched to that permco, *even for patents not included in the NBER data*. This step allows us to draw on the extensive data cleaning and matching project undertaken by Hall and Trajtenberg (2001) while at the same time identifying some errors in the NBER database. For example, patent 4,994,660 was assigned to General Electric but is identified in the NBER data as being assigned to Hitachi, Ltd. Because our algorithm relies on name matching, and the assignee name in that patent is General Electric, the patent is correctly identified in our data.

The first step only helps us match assignees with patenting activity during the period covered by the NBER database. We therefore proceed with a second step to match remaining assignee names. We do this with a name matching algorithm based on code written by Jim Bessen, available at `http://goo.gl/m4AdZ`. The algorithm uses a score based on the inverse word frequency to match assignee names to possible company names. For example, the word "American" is quite common in company names, and so contributes little to name matching; the word "Bausch" is quite uncommon, so it is given much more weight. Visual inspection of the matched names confirms very few mistakes in the matching.

Finally, we identify the top 250 assignees (by patents) with no CRSP matches. We manually matched these to CRSP whenever possible. Examples of firms requiring manual matching include research subsidiaries such as 3M Innovative Properties Company, which was not successfully matched to CRSP because its name differs substantially from its parent. Although we only checked 250 assignees, this manual check allowed us to match an additional 64,000 patents. Firms with high patenting activity but not matched to CRSP are either private companies or foreign firms that are not listed on U.S. exchanges, an example of which is Hoffmann-La Roche, the large Swiss drug company.

B.3 Correcting grant dates

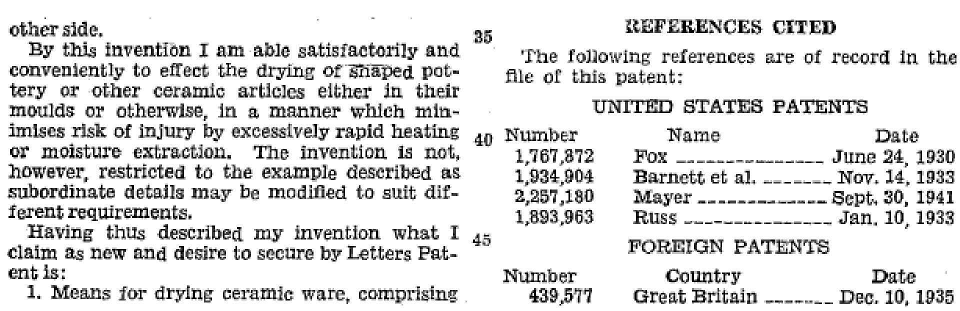
The filing and grant dates of the patents are subject to the same sort of OCR errors as the assignee information. The grant dates are particularly important for our purposes because we use them to calculate the return around the grant date. Since patent numbers are sequential by grant dates, it is easy to infer missing or incorrect grant dates by comparing patent dates to the grant dates of adjacent patents. The same is not true of filing dates, but do not use filing dates in our current work.

To populate missing patent dates and correct mistakes we identify the 3 non-missing grant dates immediately preceding and following each patent. For example, if patent k's grant date is missing but patents $(k-3,\ldots,k-1,k+1,\ldots,k+3)$ have grant date D, then we set patent k's grant date to D. By applying this procedure iteratively we are able to correct most grant dates, with the exception of patents whose grant dates are missing and lie at a boundary between two grant dates. We fill in these missing boundary dates by manually checking their grant dates on the USPTO's web site.

While we don't rely on filing dates in the paper, it is possible to correct large errors in filing dates by identifying cases where filing dates occur after the grant date, or much earlier than the filing dates of adjacent patents. These errors often occur only in the year, so we can keep the recorded month and day the same while setting the year of the patent filing to the median filing year of a 20-patent window centered on a patent with an apparent error.

B.4 Extracting citations

Extracting patent citations from the patent text documents presents another challenge. The format of a patent document has changed several times, as has the location and formatting of citations within the document. For example, Figure 5 shows the references section of patent 2,423,030, granted in 1947. The format seen here is the first format used after patent citation began in February, 1947.


other side.

By this invention I am able satisfactorily and conveniently to effect the drying of shaped pottery or other ceramic articles either in their moulds or otherwise, in a manner which minimises risk of injury by excessively rapid heating or moisture extraction. The invention is not, however, restricted to the example described as subordinate details may be modified to suit different requirements.

Having thus described my invention what I claim as new and desire to secure by Letters Patent is:

1. Means for drying ceramic ware, comprising

REFERENCES CITED

The following references are of record in the file of this patent:

UNITED STATES PATENTS

Number	Name	Date
1,767,872	Fox	June 24, 1930
1,934,904	Barnett et al.	Nov. 14, 1933
2,257,180	Mayer	Sept. 30, 1941
1,893,963	Russ	Jan. 10, 1933

FOREIGN PATENTS

Number	Country	Date
439,577	Great Britain	Dec. 10, 1935

Figure 5: A patent citation section

A human reader has no problem identifying the citations in this patent. But to understand the considerable challenge faced in automating this identification, consider the OCR for this part of the patent:

```
other side. 35 REFERENCES CITED
By this invention I am able satisfactorily and The following references are of record in the
conveniently to effect the drying of'Shaped pot- jjle of tllis patent:
tery or other ceramic articles either in their
moulds or otherwise, in a manner which min- UNITED STATES PATENTS
imises risk of injury by excessively rapid heating 40 Number Name Date
or moisture extraction. The invention is not, 1,767,872 Pox June 24, 1930
however, restricted to the example described as 1^934,904 Barnett et al Nov. 14', 1933
subordinate details may be modified to suit dif- 2,257,180 Mayer Sept. 30, 1941
ferent requirements. 1,893,963 Russ Jan. 10,1933
Having thus described my invention what I 45
claim as new and desire to secure by Letters Pat- * ("uu-^ f A 1 Jun 11>
entis: Number Country Date
1. Means for drying ceramic ware, comprising 439,577 Great Britain Dec. 10,1935
```

Our approach is to identify any text that could be a patent number (a 6- or 7-digit number, perhaps separated by commas, spaces, or other "noise" characters) and is closely followed by the correct grant date for the cited patent. In particular, for every potential patent number we identify, we determine its grant date and then search near the possible citation for that date. If the date appears, we can be very confident that we have correctly identified a citation. For example, for the patent shown in Figure 5 we extract the patent number 1,767,872 and then confirm that its grant date—June 24, 1930—appears somewhere nearby in the text. By using this two-step process to identify citations, our citation extraction is of very high quality—the probability that some random 7-digit number will be followed closely by the correct date is clearly extremely small.

Our citation extraction method provides more citations than what is available on the Google summary page. For example, the Google summary page for the patent shown in the previous example provides no citations at all, while our algorithm correctly extracted all four citations. (We exclude citations to foreign patents, as these patents are not in our database.) In general, Google does not currently report out-cites from patents granted before 1976, so we use this extraction method on all patents granted between 1926 and 1975.

B.5 Data validation

As previously mentioned, any data extraction project such as this can lead to two types of errors: matching a patent to a firm that is not the assignee, or failing to match a patent to a any firm when it does have an assignee. Our strategy makes the first error very unlikely, as a match occurs only when a name closely resembling a CRSP company name appears around the word "assignee" at the beginning of patent document. We cannot be sure how many errors of the second type we made, but we have taken care to ensure that our algorithms allow as flexible matching as possible.

We also did two final checks to check the quality of our matching strategy. First, we visually inspected a random sample of 500 patents granted between 1926 and 1975 and confirmed that assignees had been correctly extracted, and correctly matched if the assignee appeared in CRSP. This is obviously a very small sample of patents, but this careful check confirmed that no serious errors existed.

Second, we applied the extraction and matching algorithms we used in the pre-1976 period to a random sample of 25,000 patents granted between 1976 and 1999. We then compared our matches to the matches in the NBER data. None of our matches was incorrect, and only 3 patents were incorrectly not matched to an assignee. In other words, applying the techniques we used on pre-1976 data to data from the NBER period yields results that are virtually identical to those in the NBER database.

C Additional Results and Descriptive Statistics

C.1 Alternative Distributional Assumptions

Here, we briefly describe how we allowed for different distributional assumptions to construct the filtered value of a patent.

Allowing for a non-zero mean

We now assume that patent value is drawn from a non-zero mean distribution, i.e., $v_j \sim N(\mu, {\sigma_{vj}}^2)$, truncated at zero. In this case, the filtered value of v_j as a function of the stock return is equal to

$$E[v_j|r_j^l] = (1-\delta_j)\mu_j + \delta_j\, r_j^l + \sqrt{\delta_j}\,\sigma_{\xi j}\,\frac{\phi(R_j)}{1-\Phi(R_j)},$$

where ϕ and Φ are the standard normal pdf and cdf, respectively, and R and δ are the normalized return and the signal-to-noise ratio respectively,

$$R_j = -\frac{(1-\delta_j)\mu_j + \delta_j\, r_j^l}{\sqrt{\delta_j}\sigma_{\xi j}},$$

and δ_j is the signal-to-noise ratio as defined in the paper.

Relative to the paper, however, the additional issue we need to worry about is how to estimate μ_j. Following the same procedure as the paper to allow the mean μ to vary by firm and year is not possible, since at higher frequencies the standard deviation term dominates the mean. Hence, we will need additional assumptions to recover μ_j. We will do so in two ways. In both methods it is useful to note that the average stock return on patent announcement dates equals

$$E[r_j] = E[v_j] = \mu_j + 0.7979\,\sigma_{vj}$$

1. The first way assumes that μ is constant across firm-years. In this case, we estimate μ_j by first subtracting $0.7979\,\sigma_{vft}$ from firm returns on patent announcements, and then estimate μ_j as the difference in average returns on announcement versus non-announcement days using the full sample. Our point estimates imply a $\mu_j = -0.6\%$. We use this estimate when forming the conditional value of a patent as outlined above.

2. Alternatively, we assume that $\mu + 0.7979\,\sigma_v$ is constant across firm-years. That is, we allow

μ to vary exactly with σ_v. In this case, we estimate the difference in average returns on announcement versus non-announcement days using the full sample. The point estimate is 0.02%. We then recover our estimate $\mu_j = 0.0002 - 0.7979\,\sigma_{vj}$.

We find that in both of the cases above, our results are very similar to the benchmark case where we assume $\mu = 0$. Specifically, the correlation between the filtered value of the patent $E[v_j|r_j^l]$ constructed using different assumptions on μ in (a) and (b) above with our benchmark values are in excess of 99%. Indeed, allowing the pre-truncation mean to vary has mostly a scaling effect on our estimates. Since the results are essentially extremely similar to the paper, we do not reproduce them here.

Exponential

As before, we assume that the stock return of the firm on the patent grant date is given by

$$r = v + \varepsilon.$$

We now assume that v is exponentially distributed with parameter $1/\sigma_v$. As in the paper, we still assume the noise term is normally distributed, $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. Under these assumptions, we can solve for the conditional expectation – equivalent of equation (4) in the paper – in closed form,

$$E[v|R] = R + \sigma_\varepsilon \left(\sqrt{\frac{2}{\pi}} \frac{\exp(-\tilde{R}^2/2)}{G^c(\tilde{R}/\sqrt{2})} - \frac{\sigma_\varepsilon}{\sigma_v} \right)$$

where G^c is the complementary error function and

$$\tilde{R} = \frac{\sigma_\varepsilon}{\sigma_v} - \frac{r}{\sigma_\varepsilon}.$$

As in the paper, we assume that the ratio $\sigma_v^2/\sigma_\varepsilon^2$ is constant across firms. We use our estimates from section 1.4, which imply $\sigma_v^2/\sigma_\varepsilon^2 = 0.0142$, so we use that as our baseline case.

Cauchy

As before, we assume that the stock return of the firm on the patent grant date is given by

$$r = v + \varepsilon.$$

where now v is distributed according to the positive part of a Cauchy distribution centered at zero with scale parameter γ_v and ε follows a Cauchy distribution centered at zero with scale parameter γ_ε. In this case, r on announcement date is also Cauchy with scale $\gamma_v + \gamma_\varepsilon$. Under the assumption that both ε and v are Cauchy distributed, the conditional value of the patent is now given by:

$$E(v|r) = \frac{\left(\gamma_\varepsilon\ \left(c(r) - {\gamma_v}^2\right) \ln\left(c(r)\right) + 2\,r\left(c(r) + {\gamma_v}^2\right) \arctan\left(\frac{r}{\gamma_\varepsilon}\right) - 2\,\gamma_\varepsilon\ \left(c(r) - {\gamma_v}^2\right) \ln\left(\gamma_v\right) + r\pi\ \left(r^2 + (\gamma_\varepsilon - \gamma_v)^2\right)\right)\gamma_v}{\left(2\,\gamma_\varepsilon\,\gamma_v\,r \ln\left(c(r)\right) + 2\,\gamma_v\ \left({\gamma_v}^2 - \gamma_\varepsilon^2 + r^2\right) \arctan\left(\frac{r}{\gamma_\varepsilon}\right) - 4\,\gamma_\varepsilon\,\gamma_v\,r \ln\left(\gamma_v\right) + \pi\ \left(\gamma_v + \gamma_\varepsilon\right)\left(r^2 + (\gamma_\varepsilon - \gamma_v)^2\right)\right)}$$

where

$$c(r) = r^2 + \gamma_\varepsilon^2.$$

Since the second moments of the Cauchy distribution do not exist, we need alternative ways of estimating its parameters than what we used in the text. We estimate the scale of the noise term, γ_ε, using one-half the interquartile range of firm-year idiosyncratic returns, with an adjustment similar to the equation in footnote 14 in the paper. Regarding the estimation of the noise-to-signal ratio $\tilde{\delta} = \gamma_v/(\gamma_v + \gamma_\varepsilon)$, we can no longer estimate it using equation (17) in the paper. Absent a different alternative, we use the same estimates as in the paper implying a $\tilde{\delta} = 0.014$.

Table A.1: Number of patents

Data step	Number of patents
Total downloaded patents	7,797,506
Granted in 1926 or later	6,272,428
Identified as having an assignee	4,374,524
Matched to CRSP	1,928,123
Of which:	
Present in NBER data	1,404,822
New to this paper	523,301

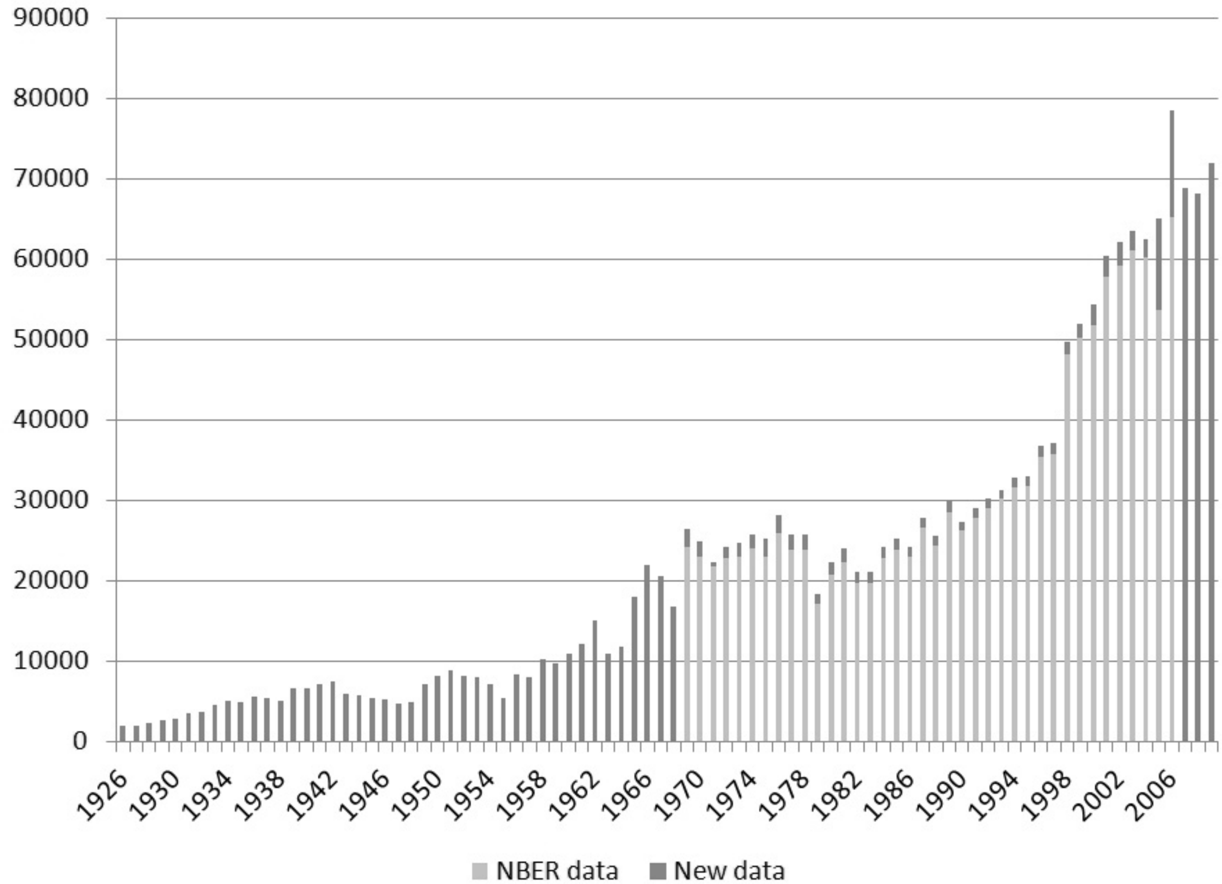
The table provides details on patents in our sample discussed in Section II.A of the paper. We begin with all patents downloaded from Google Patents, and restrict the sample to post-1926. Not all patents have assignees, and among those that do, not all are companies in CRSP. We are able to match 1,928,123 patents to CRSP firms, of which 523,301 (27%) are new to this study. Further details are reported in Table 2 and Figure 1. In the paper, we restrict attention to the patents that have a unique assignee, patents for which we have non-missing data on three day announcement return, market capitalization and return volatilities needed to compute our $\hat{\Theta}$ measure. The sample contains 1,801,879 patents.

Table A.2: Assignee matching by Decade

	Number of patents			Number of unique	
Years	Total	With assignee	Matched to CRSP	Matched firms	CRSP firms
1926–1929	174,022	48,433	8,858	182	786
1930–1939	442,700	172,925	47,029	355	951
1940–1949	307,499	141,345	60,616	451	1,042
1950–1959	425,953	171,157	82,255	587	1,246
1960–1969	567,599	265,524	165,409	1,175	3,177
1970–1979	690,459	393,661	247,102	2,086	7,204
1980–1989	708,735	579,518	235,525	2,756	11,715
1990–1999	1,109,398	933,705	352,005	3,664	14,882
2000–2010	1,846,063	1,668,256	729,324	4,415	11,900
All years	6,272,428	4,374,524	1,928,123	7,864	26,660

The table shows summary statistics for patents in our sample by decade discussed in Section II.A of the paper. Column 2 shows the total number of patents, and column 3 shows how many patents are identified as having an assignee. Column 4 shows how many of those patents with assignees are matched to a company in CRSP. (The remaining assignees are either individuals, private companies, or the matching process was unable to identify the correct company.) Columns 5 and 6 show how many unique firms there are matched to patents or in CRSP.

Figure A.1: Number of Patents with Matched Assignees



The figure shows the number of patents matched to CRSP firms by year of patent grant. Light shading denotes patents included in the NBER patent data set, while dark shading denotes patents that are new in our paper.

Table A.3: Innovation and Firm Size

Size (book assets)	**1**	**2**	**3**	**4**	**5**
Patents, citation-weighted (Θ^{cw})	1.2	2.3	3.9	8.2	90.4
Citations to Patents	2.6	2.6	2.5	2.3	2.2
Patents, citation-weighted, scaled by assets (%)	6.6	4.4	3.0	2.5	2.4
Patents, citation-weighted, scaled by mkcap (%)	7.9	6.5	5.8	5.4	22.5
Patents, SM weighted (Θ^{sm})	0.3	1.2	3.5	15.5	603.8
Total Value to Number of Patents	0.6	1.1	2.0	4.3	18.1
Patents, SM weighted, scaled by assets (%)	3.5	3.3	3.5	4.7	10.6
Patents, SM weighted, scaled by mkcap (%)	1.8	2.4	2.8	3.9	12.3
Size (Market cap of equity)	**1**	**2**	**3**	**4**	**5**
Patents, citation-weighted (Θ^{cw})	1.3	3.4	6.0	14.9	81.4
Citations to Patents	2.2	2.4	2.5	2.5	2.3
Patents, citation-weighted, scaled by assets (%)	4.0	4.4	4.0	3.4	3.1
Patents, citation-weighted, scaled by mkcap (%)	21.9	9.8	7.2	6.0	3.4
Patents, SM weighted (Θ^{sm})	0.1	0.8	2.2	9.3	618.4
Total Value to Number of Patents	0.3	0.6	1.2	2.7	19.1
Patents, SM weighted, scaled by assets (%)	1.2	2.4	3.5	4.7	13.9
Patents, SM weighted, scaled by mkcap (%)	2.4	2.9	3.1	4.3	10.6

Table reports mean value within each quintile. SM values are deflated by CPI (units are USDm in 1982). Quintiles are computed using annual breakpoints. Citation-weighted patent counts are computed as $\sum_j 1 + C_j/\bar{C}_j$ where C_j is number of cites to patent j and $\bar{C}_j$ is the mean number of cites to patents granted in the same year as patent j.

Table A.4: Firm-level innovation measure: changes in distribution across decades

Decade	Mean	Sd	p25	p50	p75	p90	p95	p99
1950	3.1	6.3	0.0	0.4	3.1	9.4	16.2	32.7
1960	4.7	10.0	0.0	0.0	4.7	14.4	23.8	51.6
1970	1.7	5.3	0.0	0.0	0.7	4.3	9.3	30.4
1980	1.2	4.0	0.0	0.0	0.0	3.1	8.1	21.7
1990	3.0	11.1	0.0	0.0	0.0	6.7	17.9	56.0
2000	5.6	19.2	0.0	0.0	1.5	14.6	32.6	86.5

Table reports the distribution of our baseline measure θ_f^{sm} across decades. Units are in percentage terms.

Table A.5: Mean innovation across industries

Ind Code	Industry Name	θ^{cw}	θ^{sm}
1	Food Products	0.76	0.98
2	Beer & Liquor	0.16	2.10
3	Tobacco Products	0.32	1.59
4	Recreation	2.19	1.39
5	Printing and Publishing	0.66	0.18
6	Consumer Goods	4.02	3.48
7	Apparel	0.51	0.22
8	Healthcare, Medical Equipment, Pharmaceutical Products	9.09	9.13
9	Chemicals	6.97	5.93
10	Textiles	1.05	0.33
11	Construction and Construction Materials	2.50	1.20
12	Steel Works Etc	1.78	1.38
13	Fabricated Products and Machinery	6.67	3.66
14	Electrical Equipment	8.09	4.58
15	Automobiles and Trucks	4.67	2.72
16	Aircraft, ships, and railroad equipment	6.22	3.85
17	Precious Metals, Non-Metallic, and Industrial Metal Mining	0.52	0.32
18	Coal	0.23	0.09
19	Petroleum and Natural Gas	0.72	1.43
21	Communication	0.41	0.67
22	Personal and Business Services	2.15	2.25
23	Business Equipment	7.45	7.19
24	Business Supplies and Shipping Containers	2.78	2.39
25	Transportation	0.05	0.05
26	Wholesale	0.42	0.24
27	Retail	0.13	0.12
28	Restaurants, Hotels, Motels	0.05	0.03

Table reports mean value of normalized firm-level innovation θ (multiplied by 100) within each Fama-French industry (using their 30 industry classification). We exclude financial firms and utilities.

Table A.6: Estimates of Patent Value: Descriptive Statistics

Moment	C	$C/\bar{C}$	R_f	Baseline		Exponential		Cauchy	
				$E[v\|R_f]$	ξ	$E[v\|R_f]$	ξ	$E[v\|R_f]$	ξ
			(%)	(%)	USDm	(%)	USDm	(%)	USDm
Mean	10.26	1.18	0.07	0.32	10.36	0.40	12.79	0.15	5.13
Std. Dev	20.13	1.98	3.92	0.20	32.04	0.30	39.75	0.11	16.13
Percentiles									
p1	0	0.00	-9.93	0.11	0.01	0.13	0.01	0.05	0.00
p5	0	0.00	-5.15	0.14	0.04	0.16	0.05	0.06	0.02
p10	0	0.00	-3.55	0.16	0.11	0.19	0.13	0.07	0.05
p25	1	0.20	-1.67	0.20	0.73	0.24	0.89	0.09	0.33
p50	5	0.62	-0.09	0.27	3.22	0.33	3.95	0.13	1.52
p75	11	1.38	1.62	0.37	9.09	0.46	11.23	0.18	4.45
p90	24	2.78	3.82	0.53	22.09	0.66	27.28	0.27	10.95
p95	38	4.06	5.73	0.68	38.20	0.85	47.27	0.34	19.13
p99	90	8.84	11.49	1.07	121.39	1.35	150.46	0.55	60.04

The table reports the distribution of the following variables across the patents in our sample: the number of future citations till the end of our sample period C; the number of citations scaled by the mean number of cites to patents issued in the same year $\bar{C}$; the market-adjusted firm returns R_f on the 3-day window around patent grant dates; the filtered component of returns $E[v|R_f]$ related to the value of innovation – using equation (4); and the filtered dollar value of innovation ξ using equation (3) deflated to 1982 (million) dollars using the CPI. In addition to the baseline case, we also report results using two alternative distributional assumptions. First, we assume that the component of firm return due to the patent, v, is exponentially distributed with scale parameter $1/\sigma_v$. As before, we assume the signal-to-noise ratio is constant across firms; using our estimates from equation (6) in the paper, we obtain $\sigma_v/\sigma_\varepsilon \approx 0.014$, so we use that. As before, we allow σ_ε to vary by firm-year and follow the same exact procedure as in the baseline case. Second, we assume that v is distributed according to a Cauchy truncated at zero with scale γ_v, while ε is distributed according to a Cauchy with parameter γ_ε. We estimate the scale of the noise term, γ_ε, using one-half the interquartile range of firm-year idiosyncratic returns, with an adjustment similar to the equation in footnote 13 in the paper. Regarding the estimation of the noise-to-signal ratio $\delta = \gamma_v/(\gamma_v + \gamma_\varepsilon)$, we can no longer estimate it using equation (6) in the paper because the variance of the Cauchy distribution does not exist. Absent a different alternative, we use the same estimate as in the paper. We restrict attention to the patents for which we have non-missing data on three day announcement return, market capitalization and return volatilities needed to compute our $\hat{\Theta}$ measure. The sample contains 1,801,879 patents.

Table A.7: Forward Citations and Patent Market Values – Alternative Distributions

	(1)	(2)	(3)	(4)	(5)
			A. Exponential		
$\log(1+C_j)$	0.174	0.099	0.055	0.013	0.004
	(9.99)	(9.44)	(10.28)	(13.84)	(5.12)
			B. Cauchy		
$\log(1+C_j)$	0.173	0.096	0.059	0.016	0.004
	(10.25)	(9.49)	(10.35)	(12.86)	(4.84)
Controls					
Firm Market Capitalization	-	Y	Y	Y	Y
Volatility	-	-	Y	Y	-
Fixed Effects	TxC	TxC	TxC	TxC	TxC
				F	FxT

Table reports the equivalent of Table 2 in the paper under two alternative distributional assumptions. Panel A presents results under the assumption that the component of firm return due to the patent, V, is exponentially distributed with scale parameter $1/\sigma_v$. Panel B presents results under the assumption that v is distributed according to a Cauchy truncated at zero with scale γ_v, while ε is distributed according to a Cauchy with parameter γ_ε. See notes to Table A.6 for more details.

Table A.8: Innovation and Firm Profit Growth – Alternative Distributions

				A. Exponential					
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.018	0.029	0.036	0.042	0.046	-0.015	-0.029	-0.032	-0.035	-0.038
[3.61]	[4.49]	[3.74]	[3.81]	[3.60]	[-2.96]	[-5.05]	[-7.25]	[-5.98]	[-5.84]
				B. Cauchy					
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.018	0.027	0.035	0.040	0.045	-0.012	-0.024	-0.027	-0.031	-0.034
[5.74]	[5.95]	[5.18]	[4.98]	[4.97]	[-2.19]	[-3.40]	[-4.95]	[-5.05]	[-4.81]

Table reports the equivalent of Table 4, Panel A in the paper under two alternative distributional assumptions. Panel A presents results under the assumption that the component of firm return due to the patent, V, is exponentially distributed with scale parameter $1/\sigma_v$. Panel B presents results under the assumption that v is distributed according to a Cauchy truncated at zero with scale γ_v, while ε is distributed according to a Cauchy with parameter γ_ε. See notes to Table A.6 for more details.

Table A.9: Innovation and Firm Growth: Results using Alternative Scaling (Market Capitalization)

a. Profits									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.006	0.017	0.023	0.028	0.034	-0.027	-0.034	-0.038	-0.043	-0.043
[2.45]	[5.53]	[4.34]	[4.21]	[4.07]	[-5.64]	[-3.29]	[-4.14]	[-4.33]	[-4.37]
b. Output									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
-0.003	0.001	0.003	0.012	0.021	-0.041	-0.051	-0.058	-0.056	-0.064
[-1.34]	[0.27]	[0.54]	[1.60]	[2.23]	[-6.23]	[-3.52]	[-3.65]	[-3.47]	[-3.84]
c. Capital									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.003	0.007	0.011	0.015	0.021	-0.013	-0.027	-0.039	-0.050	-0.062
[1.74]	[2.19]	[2.39]	[2.58]	[2.74]	[-3.33]	[-4.94]	[-5.63]	[-6.22]	[-6.71]
d. Labor									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
-0.001	0.002	0.006	0.011	0.014	-0.019	-0.026	-0.032	-0.033	-0.032
[-0.61]	[0.79]	[1.53]	[1.92]	[1.99]	[-6.19]	[-4.61]	[-5.29]	[-4.40]	[-4.23]
e. TFPR									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.003	0.010	0.012	0.016	0.017	-0.005	-0.009	-0.013	-0.013	-0.013
[1.09]	[3.17]	[2.74]	[4.22]	[4.74]	[-2.62]	[-3.59]	[-4.53]	[-3.09]	[-2.58]

Table repeats the analysis in Table 4 in the paper. Rather than book assets, we now scale the firm's dollar value of innovation by its end of year market capitalization. Similarly, innovation by competing firms is constructed as the dollar value of innovation divided by their total market capitalization, in a manner analogous to equation (11) in the paper. See notes to Table 4 in the paper for more details.

Table A.10: Innovation and Firm Profit Growth – Patent citations measured within a fixed window

A. Citations within 3-years of patent grant									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.007	0.012	0.017	0.021	0.025	-0.005	-0.006	-0.007	-0.006	-0.006
[4.41]	[4.92]	[5.08]	[4.99]	[5.31]	[-1.85]	[-1.56]	[-1.76]	[-1.13]	[-1.06]
B. Citations within 5-years of patent grant									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.008	0.014	0.019	0.024	0.027	-0.005	-0.007	-0.009	-0.007	-0.007
[4.73]	[5.58]	[5.35]	[5.35]	[5.71]	[-1.69]	[-1.78]	[-2.11]	[-1.43]	[-1.24]
C. Citations within 10-years of patent grant									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.008	0.015	0.022	0.027	0.032	-0.003	-0.005	-0.009	-0.007	-0.007
[4.86]	[5.77]	[5.62]	[5.69]	[6.59]	[-0.89]	[-1.29]	[-2.11]	[-1.28]	[-1.23]

Table reports the equivalent of Table 5, Panel A in the paper under different ways of adjusting patent citations for truncation lags. In each of the panels A, B, and C, we measure forward citations over the first N years after the patent is issued, where $N = 3, 5, 10$. We then repeat the analysis in Table 5 by also excluding the last N years from the sample. See notes to Table 5 in the paper for more details.

Table A.11: Innovation and Firm Growth: Controlling for R&D spending of Firm and Competitors

Profits									
Firm					a. Competitors				
1	2	3	4	5	1	2	3	4	5
0.017	0.027	0.034	0.039	0.043	-0.018	-0.034	-0.037	-0.040	-0.045
[3.33]	[4.12]	[3.39]	[3.48]	[3.31]	[-3.24]	[-5.42]	[-8.23]	[-6.36]	[-6.38]
b. Output									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.008	0.013	0.018	0.022	0.028	-0.016	-0.034	-0.044	-0.048	-0.056
[2.85]	[3.07]	[2.85]	[2.62]	[3.15]	[-3.64]	[-6.33]	[-8.43]	[-7.91]	[-7.98]
c. Capital									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.010	0.021	0.028	0.034	0.039	0.002	-0.005	-0.012	-0.020	-0.029
[8.40]	[6.69]	[5.76]	[4.40]	[4.13]	[0.38]	[-0.82]	[-1.59]	[-2.35]	[-3.15]
d. Labor									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.007	0.014	0.019	0.023	0.025	-0.007	-0.017	-0.021	-0.021	-0.019
[5.65]	[4.39]	[4.11]	[3.76]	[3.30]	[-1.64]	[-3.86]	[-4.34]	[-3.67]	[-3.00]
e. TFPR									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.012	0.015	0.017	0.021	0.022	-0.001	-0.006	-0.010	-0.015	-0.017
[2.18]	[2.07]	[2.56]	[3.28]	[3.98]	[-0.52]	[-2.20]	[-3.20]	[-4.59]	[-4.09]

Table repeats the analysis of Table 4 in the paper including the firm's R&D spending as an additional control. We control for the firm's ratio of R&D spending to sales, as well as the ratio of total R&D spending to total sales of competing firms. See notes to Table 4 in the paper for additional details.

Table A.12: Innovation and Firm Growth: Controlling for Measures of Investor Attention

Horizon	1	2	3	4	5
	A. Control for number of WSJ articles				
Firm	0.017	0.030	0.036	0.043	0.045
	[2.60]	[4.31]	[2.89]	[3.23]	[3.12]
Competitor	-0.033	-0.053	-0.047	-0.057	-0.074
	[-13.84]	[-5.67]	[-5.53]	[-6.45]	[-6.78]
N	28966	26293	24077	19541	15529
	B. Control for number of analysts				
Firm	0.011	0.018	0.022	0.026	0.028
	[2.66]	[4.45]	[3.50]	[3.37]	[3.07]
Competitor	-0.020	-0.040	-0.042	-0.042	-0.046
	[-2.47]	[-5.36]	[-7.12]	[-5.38]	[-4.99]
N	77483	69322	62209	55734	49858
	control for institutional ownership				
Firm	0.019	0.029	0.036	0.040	0.042
	[3.18]	[4.51]	[3.70]	[3.23]	[3.00]
Competitor	-0.015	-0.032	-0.034	-0.037	-0.040
	[-2.26]	[-4.33]	[-5.68]	[-4.53]	[-4.61]
N	70874	61737	53941	47165	41338

Table repeats the analysis in Table 4 in the paper using additional controls for the degree of investor attention. In panel A we control for the (log one plus the) number of articles that mention the firm in the Wall Street Journal. The data is available over the 2000-2007 period. The data is from matching news articles in Factiva to firms following the procedure in Butler and Gurun, 2012. In Panel B, we control for the (log of one plus the) number of analysts covering the stock. The data is from I/B/E/S and covers the 1975-2010 period. In Panel C, we control for the fraction of institutional ownership. The data is from Thomson Reuters Institutional (13f) Holdings - Stock Ownership Summary and covers the 1980-2010 period. See the notes to Table 4 in the paper for additional details.

Table A.13: Innovation and Firm Growth: IV using tax price of R&D

Profits									
Firm					a. Competitors				
1	2	3	4	5	1	2	3	4	5
0.116	0.221	0.273	0.352	0.409	-0.116	-0.207	-0.266	-0.327	-0.373
[1.92]	[2.09]	[1.94]	[1.93]	[1.75]	[-2.54]	[-2.50]	[-2.37]	[-2.30]	[-2.08]
b. Output									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.069	0.099	0.148	0.208	0.262	-0.070	-0.134	-0.187	-0.233	-0.273
[1.91]	[1.60]	[1.67]	[1.76]	[1.69]	[-2.29]	[-2.49]	[-2.44]	[-2.35]	[-2.16]
c. Capital									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.076	0.128	0.176	0.233	0.296	-0.092	-0.171	-0.242	-0.319	-0.386
[2.12]	[2.02]	[2.00]	[2.04]	[1.97]	[-2.99]	[-3.06]	[-3.08]	[-3.12]	[-2.94]
d. Labor									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.052	0.083	0.113	0.148	0.195	-0.073	-0.139	-0.181	-0.213	-0.233
[1.64]	[1.43]	[1.39]	[1.39]	[1.39]	[-2.55]	[-2.76]	[-2.55]	[-2.28]	[-1.95]
e. TFPR									
Firm					Competitors				
1	2	3	4	5	1	2	3	4	5
0.092	0.149	0.170	0.212	0.229	-0.063	-0.095	-0.117	-0.130	-0.142
[2.26]	[2.44]	[2.31]	[2.38]	[2.16]	[-1.81]	[-1.77]	[-1.78]	[-1.65]	[-1.55]

Table repeats the analysis of Table 4 in the paper using instrumental variables. We use the R&D tax credit variation as an instrument for our innovation measure, following Bloom, Schankerman, and Van Reenen (2013). This R&D price is constructed at an annual level for each firm using state-level R&D tax credits. See Bloom et al. (2013) for more details on the construction of this variable. We instrument for the firm's own innovation θ_{ft} using the firm-level tax price; we instrument for the innovation by competing firms $\theta_{I\setminus f,t}$ using the average R&D price of competing firms. The first-stage F statistics vary from 17.1 to 61 across specifications and horizons. We cluster standard errors by firm. See notes to Table 4 in the paper for additional details.

Table A.14: Industry Output and Innovation – Comparison with Citation-Weighed Patents

Horizon (years)	1	2	3	4	5	6	7	8
	A. Industry output (quantity)							
SM	0.005	0.009	0.013	0.018	0.026	0.042	0.055	0.065
	[2.73]	[2.49]	[2.83]	[3.02]	[3.29]	[3.49]	[3.32]	[3.23]
R-sq	0.054	0.085	0.119	0.150	0.183	0.217	0.241	0.261
CW	0.007	0.016	0.024	0.031	0.038	0.044	0.049	0.053
	[3.07]	[3.61]	[4.05]	[4.11]	[3.96]	[3.81]	[3.61]	[3.29]
R-sq	0.051	0.086	0.119	0.148	0.176	0.197	0.215	0.229
	B. Industry output (value added)							
SM	0.001	0.002	0.004	0.007	0.012	0.027	0.038	0.047
	[0.61]	[0.44]	[0.64]	[0.79]	[1.15]	[2.35]	[2.78]	[2.83]
R-sq	0.014	0.027	0.044	0.059	0.077	0.098	0.121	0.140
CW	0.004	0.009	0.013	0.017	0.021	0.025	0.028	0.027
	[1.57]	[1.75]	[1.77]	[1.76]	[1.78]	[1.75]	[1.68]	[1.45]
R-sq	0.015	0.029	0.045	0.060	0.077	0.092	0.109	0.122
N	1395	1364	1333	1302	1271	1240	1209	1178

Table reports the relation between innovation and output growth at the industry level. We construct industry-level innovation indices as

$$\theta^i_{I,t} = \frac{\sum_{f \in I} \Theta^i_{f,t}}{\sum_f B_{ft}},$$

using both the market based measure ($i = sm$) as well as for cohort-adjusted, citation-weighted patent counts ($i = cw$). We report the estimated coefficients a_τ from a specification similar to equation (12) in the paper,

$$x_{t+\tau} - x_t = a_0 + a_\tau\, \theta^i_{I,t} + \rho x_t + Z_{It} + u_{t+\tau}.$$

where x is log industry output (quantity in Panel A, value added in Panel B) and Z is a vector of controls that includes log capital, log employment, mean industry id. volatility and time effects. We compute standard errors using Newey-West. To compare across the two measures, we scale $\theta^i_{I,t}$ to unit standard deviation.

Table A.15: Innovation and Aggregate Growth – Comparison with Citation-Weighted Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Aggregate Output							
χ^{cw}	0.005	0.009	0.013	0.015	0.017	0.022	0.023	0.022
	[1.08]	[1.10]	[1.36]	[1.40]	[1.70]	[2.31]	[2.24]	[2.13]
R-sq	0.078	0.113	0.19	0.254	0.289	0.347	0.373	0.423
	B. Aggregate TFP							
χ^{cw}	0.004	0.007	0.011	0.016	0.02	0.022	0.023	0.026
	[2.30]	[2.20]	[2.27]	[2.94]	[3.12]	[3.14]	[3.33]	[3.89]
R-sq	0.201	0.305	0.397	0.493	0.535	0.559	0.592	0.652

Table repeats the analysis of Figure 5 in the paper using an alternative index of innovation that is constructed using patent citations. Specifically, in a direct analogy to equation (18) in the paper, the value of the index in year t is given by

$$\chi_t^{cw} = \frac{\sum_{j \in J_t} \hat{C}_j}{Y_t},$$

where $\hat{C}$ is the number of citations to patent j in the first 10 years since its grant date, J_t is the set of patents issued in year t (including both private and public firms) and Y is aggregate output. Due to truncation, the sample ends in 2000. We report the estimated coefficients a_τ from the following specification

$$x_{t+\tau} - x_t = a_0 + a_\tau \, \log \hat{\chi}^{cw} + \sum_{l=0}^{L} c_l \, x_{t-l} + u_{t+\tau}.$$

Here, x is log aggregate output (panel A) or log TFP (panel B). We scale $\log \hat{\chi}^{cw}$ to unit standard deviation. We examine horizons of one to five years. We select the number of lags L using the BIC criterion, which advocates a lag length of one to two years depending on the specification. We compute standard errors using Newey-West.

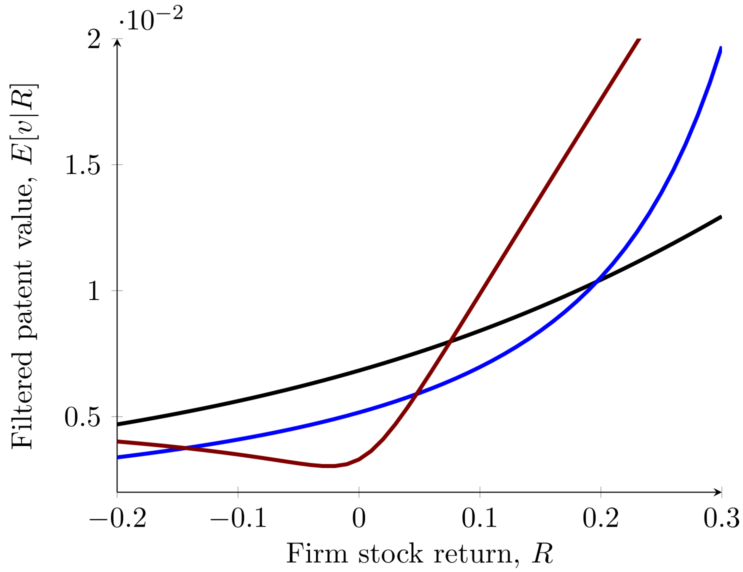


Figure A.2: Plot compares the filtered values, $E[v|R]$ across three different assumptions: our baseline case (black); the assumption that v is exponentially distributed (blue); the assumption that ε is Cauchy distributed and v follows a truncated Cauchy (at zero). See notes to Table A.7 for more details on the estimation of the parameters. We use the sample mean for the variance (or scale) of the error term to draw these graphs. We use the implied estimates from equation (6) in the main text to calibrate δ across the three cases.

Figure A.3: Innovation and Aggregate Growth – VAR results

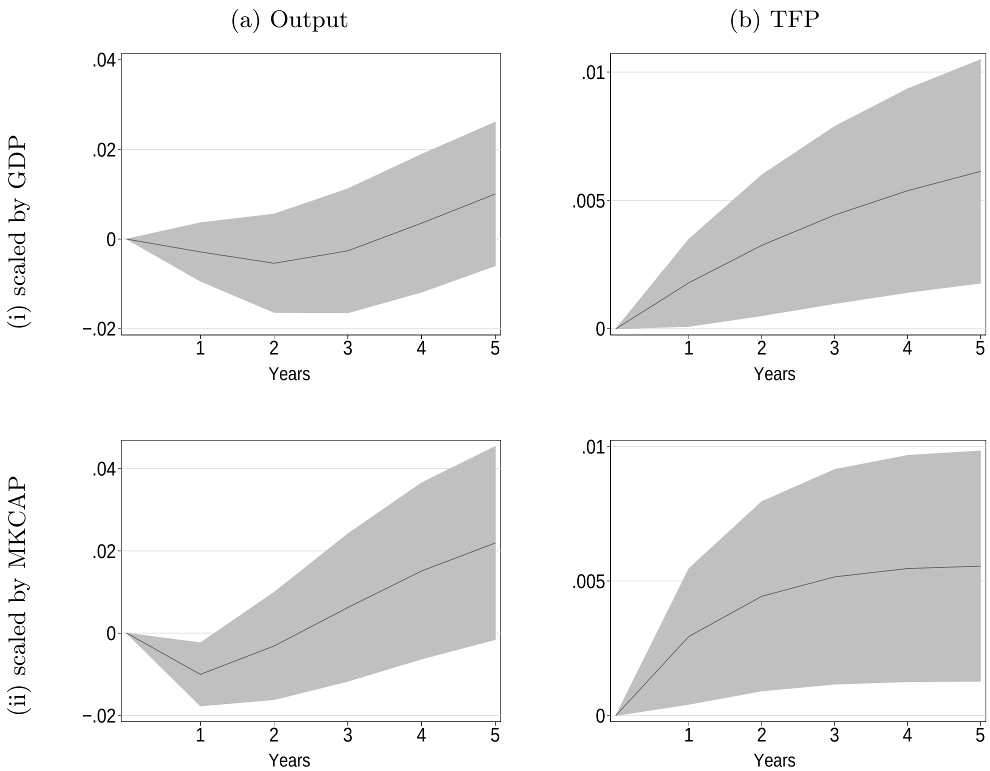


Figure shows impulse response of output per capita and productivity to innovation using bi-variate VARs. We obtain impulse responses by ordering our innovation measure last. We select lag length based on the BIC criterion. Dotted lines represent 90% confidence intervals using standard errors are computed using 500 bootstrap simulations. Productivity is utilization-adjusted TFP from Basu, Fernald, and Kimball (2006). Output is gross domestic product (NIPA Table 1.1.5) divided by the consumption price index (St Louis Fed, CPIAUCNS). Output per capita is computed using population from the U.S. Census Bureau.

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