TECHNOLOGICAL INNOVATION, RESOURCE ALLOCATION, AND GROWTH

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TECHNOLOGICAL INNOVATION, RESOURCE ALLOCATION, AND GROWTH

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We propose a new measure of the economic importance of each innovation. Our measure uses newly collected data on patents issued to U.S. 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 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 Codes:* G14, E32, O3, O4.

I. Introduction

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 because of 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 article 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 data set 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

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1. Several new studies exploit the same source of patent data (Google Patents) as we do in our article. For instance, see Moser and Voena (2012), Moser, Voena, and Waldinger (2012), and Lampe and Moser (2014). Ours is the first to exploit this data at a large scale and match them to firms with stock price data.

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), and Scherer (1965, 1983) who describe firms that have conducted radical innovation and have been responsible for technical change in the United States.

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, Jaffe, and Trajtenberg (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; Grossman and Helpman 1991; Aghion and Howitt 1992; Klette and Kortum 2004). Since the value of a firm's

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2. For instance, Hall, Jaffe, and Trajtenberg (2005) and Nicholas (2008) document that firms owning highly cited patents have higher stock market valuations. Harhoff et al. (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 data set that includes estimates of patent values based on licensing fees and show that the relation between private values and patent citations is nonmonotonic. Our approach allows us to revisit this question at a higher level of granularity than Hall, Jaffe, and Trajtenberg (2005), while using a broader sample than Harhoff et al. (1999), Moser, Ohmstedt, and Rhode (2011), and Abrams, Akcigit, and Popadak (2013).

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 total factor 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—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, Jaffe, and Trajtenberg 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 vector autoregressions (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 article 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 Pakes 1985; Austin 1993; Hall, Jaffe, and Trajtenberg 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 use to study different issues in the literature on innovation and growth.

Our article 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 Simon and Bonini 1958). Our article 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 et al. 2011; Garcia-Macia, Hsieh, and Klenow 2015). Existing approaches rely on calibration or estimation of structural models. In contrast,

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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 U.S. patent office (see 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.

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 article is also related to work that examines whether technological innovation leads to positive knowledge spillovers or business stealing. Related to this study 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. Finally, this work is also related to the productivity literature that has documented substantial dispersion in measured productivity across plants and firms (see 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.

II. 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 U.S. 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.

II.A. 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 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 provide a matched permco for 44.1% of all patents with an

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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.

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 six- or seven-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.

assignee and 31% of all granted patents. By comparison, the NBER patent project provides a match for 32% of all patents from 1976 to 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 to 1929, he matches 9,707 patents, while our database includes 8,858 patents; from 1930 to 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 nonmissing market capitalization in CRSP, and for which we can compute return volatilities, we obtain a final sample of 1,801,879 patents.

II.B. Identifying Information Events

The first step in constructing our measure is to isolate the release of information to the market. The 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 II.D.

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

$$(1) \qquad \Delta V_j = (1 - \pi_j)\xi_j,$$

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 equation (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 I, 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 a 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 18 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 because 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 Lamont and Frazzini (2007).
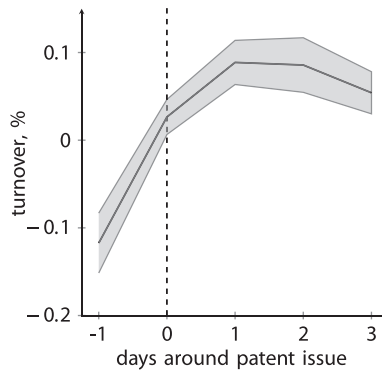
Share Turnover during Patent Issuance Weeks

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.

II.C. *Some Illustrative Examples*

Before turning to our main analysis, we 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% (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 et al. (1988), was published in *Science* and has since been cited over 1,300 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% 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% 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 three-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.

II.D. 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

$$(2) \qquad R_j = v_j + \varepsilon_j,$$

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:

$$(3) \qquad \xi_j = (1 - \bar{\pi})^{-1} \frac{1}{N_j} E[v_j | R_j] \, M_j.$$

If multiple patents N_j are issued to the same firm on the same day as patent j, we assign each patent a fraction $\frac{1}{N_j}$ of the total value. Since the unconditional probability $\bar{\pi}$ of a successful patent application is approximately 56% in the 1991–2001 period (see Carley, Hegde, and Marco 2015), we account for this understatement by multiplying our estimates of patent values by $\frac{1}{0.44} = 2.27$.[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

To implement equation (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 0, $v_j \sim \mathcal{N}^+(0, \sigma_{vft}^2)$.[10] Further, we assume that the noise term is normally distributed, $\varepsilon_j \sim \mathcal{N}(0, \sigma_{\varepsilon ft}^2)$. Given our assumptions, the filtered value of v_j as a function of the idiosyncratic stock return R is equal to

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

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

$$(5) \qquad \delta_{ft} = \frac{\sigma_{vft}^2}{\sigma_{vft}^2 + \sigma_{\varepsilon ft}^2}.$$

The conditional expectation in equation (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]

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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, Hegde, and Marco (2015) use proprietary data 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 the post-2000 period, these data contain unreliable information on assignee names that is required to match the patents to firms. We return to this issue in Section IV.B.

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. (i) We allowed for a nonzero 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 nonzero mean had mostly a scaling effect on our estimates: the correlation of filtered returns in equation (4) was in excess

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 $\sigma_{\varepsilon ft}^2$ and σ_{vft}^2 are allowed to vary across firms and time, but in constant proportions to each other. To estimate 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},

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

where R_{fd} refers to the three-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 equation (4) involves estimating the variance of the measurement error $\sigma_{\varepsilon ft}^2$. We do so nonparametrically using the sum of squared market-adjusted returns, and we allow the estimate to vary at an annual frequency (see Andersen and Terasvirta 2009).[13]

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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 because 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 article, we also approximated equation (4) with a piecewise linear function, $\max(0, R)$; the correlation between this approximation and our filtered returns in equation (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.

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_{ft}^2. This second moment is

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 (AIPA), which came into effect 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. 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]

To examine the importance of this issue, we exploit the change in information disclosure policy by the AIPA that applied to all patents filed after November 30, 2000. For the patents that were filed after November 30, 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 30, 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 equation (6) across the two sets of patents: patents filed just before the act, that is, in the month of November 2000; and patents filed immediately after the act, that is, in December 2000. Using

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estimated over both announcement and nonannouncement days, so it is a mongrel of both σ_{vft}^2 and $\sigma_{\varepsilon ft}^2$. Given our estimate of σ_{ft}^2, 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 $\sigma_{\varepsilon ft}^2 = 3\,\sigma_{ft}^2\,\left(1 + 3\,d_{ft}\,(e^{\hat{\gamma}} - 1)\right)^{-1}$.

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 $\Delta V_{jt} = (1 - \pi_j)\,\xi_j + \pi_j\,(\xi_j - \hat{\xi}_j)$, 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 equation (6) to estimate δ.

TABLE I

ESTIMATES OF PATENT VALUE: DESCRIPTIVE STATISTICS

Moment	C	$\frac{C}{\overline{C}}$	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

Notes. 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 $\overline{C}$; the market-adjusted firm returns R_f on the three-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 three-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 nonmissing 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.

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 .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]

II.E. *Descriptive Statistics*

In Table I we report the sample distribution of ξ along with other variables: the number of forward citations, the idiosyncratic

15. Nevertheless, we do investigate the robustness of our results to different values of δ. As noted already, 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 on request.

firm returns R_f, and filtered patent values obtained from equation (4). As is well known, the distribution of patent citations is highly skewed, with approximately 16% of patents receiving no citations. In addition, the distribution of firm returns R_f is right skewed, and positive roughly 55% of the time. In addition, the estimated value of patents—both in absolute terms ξ as well as relative to the firm market capitalization in equation (4)—is 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, 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.

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 attach higher valuations to individual patents compared to the inventors in the sample of Giuri et al. (2007). In addition, the distributional assumptions we made in equation (4) likely 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

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16. For instance, allowing the mean of the distribution of v_j (before truncation) to vary from 0 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.

with the other commonly used measure of patent quality, forward citations.

III. 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, Jaffe, and Trajtenberg (2005) and Nicholas (2008) have argued that forward citations are also correlated with the private value of patents based on a regression of a firm's Tobin's Q on its stock of citation-weighted patents. Harhoff et al. (1999) and Moser, Ohmstedt, and Rhode (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, Akcigit, and Popadak (2013) cast doubt on these earlier findings by proposing a model of defensive patenting. Using a proprietary data set 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 reexamine the relation between citations and the market value of innovation using the number of citations the patent receives in the future. Our measure allows us to study this question at a more granular level than Hall, Jaffe, and Trajtenberg (2005), while using a broader sample than Abrams, Akcigit, and Popadak (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,

$$(7) \qquad \log \xi_j = a + b \log\left(1 + C_j\right) + c\, Z_j + u_j.$$

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 $\log M_j$ (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

TABLE II

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

Notes. 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 II.D. We include grant year fixed effects throughout. Depending on the specification we also include: USPTO three-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 parentheses. 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.

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 II. Consistent with the findings of Harhoff et al. (1999) and Hall, Jaffe, and Trajtenberg (2005), we find a strong and positive association between forward citations and market values. Figure II 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

17. As Table I 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
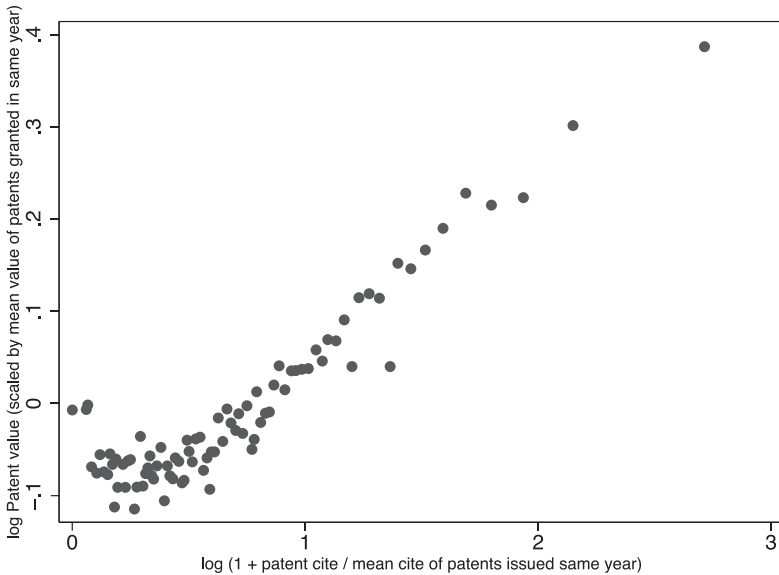
FIGURE II

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 ($1 + \frac{C}{\bar{C}}$). The horizontal axis plots the log of average cohort adjusted patent citations in each quantile. The vertical axis plots the log 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).

pattern is somewhat at odds with the findings of Abrams, Akcigit, and Popadak (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, Akcigit, and Popadak (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

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to differentiate among these patents. In contrast, our measure indicates some variation in quality among these less-cited patents. The nonlinearity 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.

associated with a 0.1% to 3.2% increase in the value of that patent, depending on the controls included. For comparison, Hall, Jaffe, and Trajtenberg (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 \$15,000 to \$500,000 (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 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 III, we plot the distribution of the estimated coefficients and t-statistics corresponding to the specification in column (5) of Table II. Based on the distribution of coefficients and t-statistics across the placebo experiments, centered at zero, relative to the effects we find in Table II, 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 sizable 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.
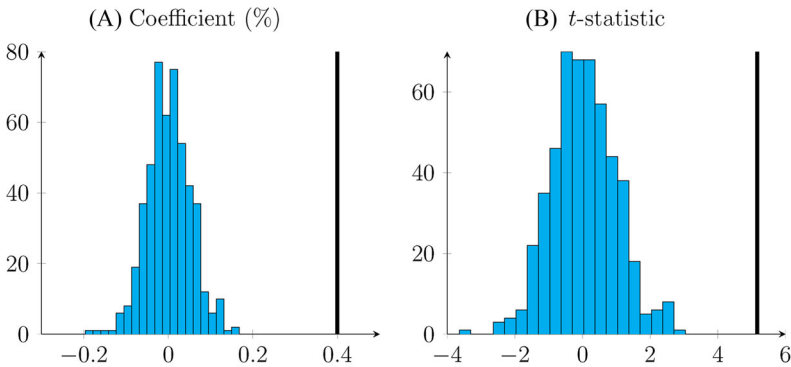
FIGURE III

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 col-
umn (5) in Table II—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 II.

IV. INNOVATION AND FIRM GROWTH

Models of endogenous growth have rich testable predictions
about the cross-section of firms, linking improvements in the tech-
nology frontier to resource reallocation and subsequent economic
growth (Romer 1990; Grossman and Helpman 1991; Aghion and
Howitt 1992; Klette and Kortum 2004). Since the value of a firm's
innovative output is hard to observe, constructing direct empiri-
cal 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 also contrast the dynamics of reallocation and
growth using our measure with the citations-based measure that
is available in the literature.

IV.A. 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
nonmissing 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,

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

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 construct an analogous measure using this metric,

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

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, Jaffe, and Trajtenberg 2005). Equations (8) and (9) are essentially weighted patent counts; if firm f files no patents in year t, both variables 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,

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

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 because we also control for various measures of firm size in all our specifications.

TABLE III

DESCRIPTIVE STATISTICS: FIRM INNOVATION AND GROWTH

	Mean	Std. dev.	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

Notes. 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 (2014). All variables are winsorized at the 1% level using annual breakpoints.

As we discuss later, the results using our measure are similar if we scale by the firm's market capitalization instead.

Table III 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 III, 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 the 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.

IV.B. 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; Grossman and Helpman 1991; Aghion and Howitt 1992; 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.

1. 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 $I \backslash f$. We then measure innovation by competitors of firm f as the weighted average of the innovative output of its competitors,

$$(11) \qquad \theta_{I \backslash f,t}^i = \frac{\sum_{f' \in I \backslash f} \Theta_{f',t}^i}{\sum_{f' \in I \backslash f} B_{f't}}.$$

We compute equation (11) for 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.

$$(12) \qquad \log X_{f,t+\tau} - \log X_{f,t} = a_\tau\, \theta_{f,t} + b_\tau\, \theta_{I \backslash f,t} + c\, Z_{ft} + u_{ft+\tau}.$$

We explore horizons τ of one to five 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 Evans 1987). Controlling for other measures of size (i.e., book assets) yields similar results. We control for firm idiosyncratic

TABLE IV

INNOVATION AND FIRM GROWTH

	Firm (Horizon)					Competitors (Horizon)				
	1	2	3	4	5	1	2	3	4	5
Panel A: Profits										
	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]
Panel B: Output										
	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]
Panel C: Capital										
	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]
Panel D: Labor										
	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]
Panel E: TFPR										
	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]

Notes. Table reports point estimates of equation [12] for firm profits, output, capital, employment, and TFPR. See notes to Table III for variable definitions. We relate firm growth and productivity to innovation by the firm (θ_f^{SM}, defined in equation [10]; see also equation [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, *t*-statistics are reported in parentheses. All right-hand-side variables are scaled to unit standard deviation.

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.

2. 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–D of Table IV 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 a 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 a 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, Schankerman, and Van Reenen 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 IV examines the relation between innovation and (revenue-based) firm productivity. We see that a one standard deviation increase in a firm's innovation is associated with a 2.4% increase in a firm's revenue-based productivity. Conversely, a one standard deviation increase in innovation by a 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

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.

of firms' economic activity remains a significant challenge.[19] A direct 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]

3. 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 V reports estimates of equation (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 IV, we note that they are smaller in magnitude, typically less than half. Specifically, a one standard deviation change in a 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 important, the results in Table V reveal no evidence for creative destruction. The estimated coefficients b are either positive or not statistically different from 0. 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

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

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%, which is between 10% and 23% of the interquartile range of TFP in their sample.

TABLE V

INNOVATION AND FIRM GROWTH (USING CITATION-WEIGHTED PATENTS)

	Firm (Horizon)					Competitors (Horizon)			
1	2	3	4	5	1	2	3	4	5
Panel 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]
Panel 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]
Panel 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]
Panel 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]
Panel 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]

Notes. Table reports point estimates of equation (12) for firm profits, output, capital, employment and TFPR. See notes to Table III 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 ($\theta_{I\backslash f}^{CW}$, 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, *t*-statistics are reported in parentheses. All right-hand-side variables are scaled to unit standard deviation.

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 reestimate equation (12) including both θ_f^{sm} and θ_f^{cw}, as well as $\theta_{I\backslash f}^{sm}$ and $\theta_{I\backslash f}^{cw}$. We report the estimation results in Table VI. We see that the relation between θ^{sm} and future firm growth and productivity is comparable to those in Table IV. By contrast, the relation between the citation-based measure and own firm growth is in many cases not statistically different from 0. By design, our measure and citation-weighted patent counts should contain independent information regarding externalities. Examining the right panel of Table VI 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

TABLE VI

INNOVATION AND FIRM GROWTH (BOTH MEASURES)

	Firm (Horizon)					Competitors (Horizon)				
	1	2	3	4	5	1	2	3	4	5
Panel A: Profits										
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]
Panel B: Output										
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]
Panel C: Capital										
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]
Panel D: Labor										
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]
Panel E: TFPR										
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]

Notes. Table relates firm growth and productivity to innovative output—equation (12)—using both the stock market (SM) and the citation-weighted measure (CW). See notes to Tables III, IV, and V for variable definitions and more details on the specification. All right-hand-side variables are scaled to unit standard deviation. *t*-statistics are reported in parentheses.

innovation output is measured using citation-weighted patent counts (θ^{cw}).

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

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.

value of innovation, we document substantial patterns of creative destruction relative to those previously documented.

4. Robustness and Caveats. The estimated value of innovative output $\theta_{f,t}^{sm}$ contains information on the firm's market valuation in the numerator but not in the denominator. Hence, one potential concern is that fluctuations in $\theta_{f,t}^{sm}$ 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 $\theta_{f,t}^{sm}$ 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 fluctuations 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

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

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 by Bloom, Schankerman, and Van Reenen (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, though the magnitudes are stronger (see Table A.13 in the Online Appendix).

V. 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 V.A, we use firm-level estimates of Section IV.B to examine the net impact of innovation on aggregate output and productivity. Second, in Section V.B, 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.

V.A. Aggregating Coefficients

As a first step in assessing the net impact of innovation, we examine what our empirical estimates in Section IV.B 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

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

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 0. Second, we aggregate these estimates across all firms in the sample to obtain the average component of aggregate growth related to innovation,

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

In equation (14), the numerator and denominator sum across all firms that survive to time τ. The term inside the brackets 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

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

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

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

and

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

When comparing our aggregate estimate of reallocation equation (15) to its realized counterpart equation (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. Although 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) includes 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.

V.B. 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 the Appendix, we provide a simple model of innovation—based on Atkeson and Burstein (2011)—that delivers an approximately

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23. We can also similarly aggregate the firm-level coefficients we obtained in Section IV.B 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 0.

linear relation between the two.[24] After discussing the descriptive properties of the index, we examine its correlation with measures of aggregate productivity and economic growth.

1. Methodology. We construct an economy-wide index of innovation as

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

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 the Appendix. 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 IV. We see that both indices line up well with the three major waves of technological innovation in the United States. 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 1930s are in the

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.

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.
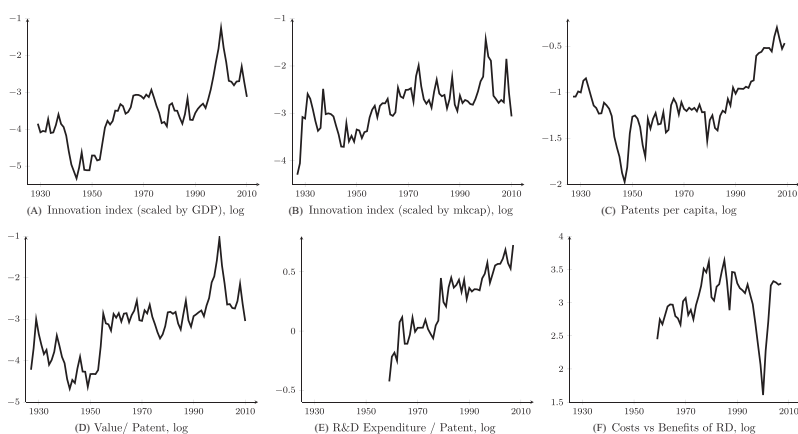
Aggregate Measures of Innovation

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 patent 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.

automobile (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 the 1960s and early 1970s—a period commonly recognized as a period of high innovation in the United States (see 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 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 toward the end of the sample.[26] In particular, post-1980, there is a rapid acceleration of 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 equation (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 on 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 United States 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

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 article, we show that our index is also related to the index of Alexopoulos and Cohen (2009).

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

2. 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 GDP deflated by the consumer price index, and productivity as the utilization-adjusted TFP from Basu, Fernald, and Kimball (2006). To study the relation between our innovation index and aggregate growth, we estimate the following specification:

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

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 Bayesian information 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 V, 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
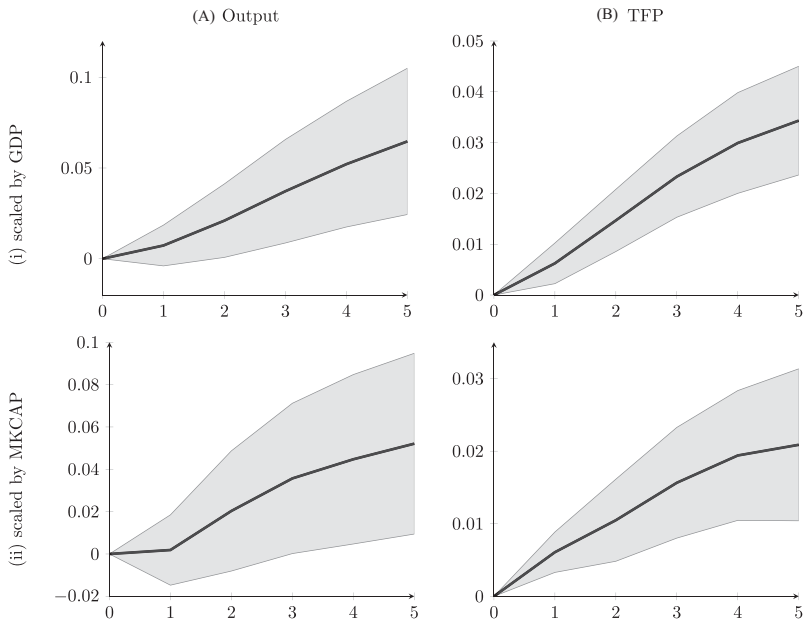
FIGURE V

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 2 plus the horizon. Productivity is utilization-adjusted TFP from Basu, Fernald, and Kimball (2006). Output is GDP (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.

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 V, 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]

28. In addition to equation (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.

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 V.A. 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.

VI. Conclusion

Using patent data for U.S. 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 article. 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., Romer 1990; Grossman

and Helpman 1991; Aghion and Howitt 1992; Klette and Kortum 2004) and are not tied to the specific model used in the article. Third, our innovation measure provides information that is complementary to the information contained in patent citations. By construction, our approach is geared toward measuring the private value of innovation; by contrast, patent citations are likely a better measure of the scientific value of the patent.

APPENDIX: A MODEL OF INNOVATION

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

A. 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

$$(20) \qquad Y_t = \left[\int_0^{H_t} \theta_j^{\frac{1}{\rho}} \left(q_{j,t} \right)^{\frac{(\rho-1)}{\rho}} dj \right]^{\frac{\rho}{(\rho-1)}}.$$

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 nondecreasing 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

$$(21) \qquad X_t \equiv \int_0^{H_t} \theta_j \, dj,$$

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

$$(22) \qquad X_t = X_{t-1} \left(1 + \chi_t \right).$$

Each good is produced according to a linear production technology,

$$(23) \qquad q_{j,t} = l_{j,t}.$$

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,

$$(24) \qquad U(C_t) = \log C_t,$$

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

B. Equilibrium

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

$$(25) \qquad p_{j,t} = \left[\frac{q_{j,t}}{Y_t} \right]^{-\frac{1}{\rho}} \theta_j^{\frac{1}{\rho}}.$$

Using (equation 25), total profits from producing good j equal

$$(26) \qquad \Pi_{j,t} \equiv p_{j,t}\, q_{j,t} - w_t\, q_{j,t} = q_{j,t}^{1-\frac{1}{\rho}} \left(Y_t\, \theta_j \right)^{\frac{1}{\rho}} - w_t\, q_{j,t}.$$

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

$$q_{j,t} = Y_t\, \theta_j \left[\frac{w_t}{1 - \frac{1}{\rho}} \right]^{-\rho}$$

$$(27) \qquad\qquad = \theta_j X_t^{-1},$$

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

$$(28) \qquad \int_0^{H_t} q_{j,t}\, dj = 1.$$

Using (equation 20), we get that aggregate output and consumption are given by

$$(29) \qquad Y_t = X_t^{\frac{1}{\rho - 1}},$$

while the equilibrium wage is given by

$$(30) \qquad w_t = \frac{\rho - 1}{\rho} Y_t,$$

and flow profits from owning a patent to good j are

$$(31) \qquad \Pi_{j,t} = \frac{1}{\rho} \theta_j Y_t^{2-\rho}.$$

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,

$$(32) \qquad \xi_{j,t} \equiv E_t \left[\sum_{s=t}^{\infty} \beta^{s-t} \frac{U'(C_s)}{U'(C_t)} \Pi_{j,s} \right] = \theta_j Y_t X_t^{-1} B,$$

where

$$(33) \qquad B = \frac{1}{\rho} E_t \left[\sum_{s=t}^{\infty} \beta^{s-t} \left(\frac{X_t}{X_s} \right) \right]$$

is a constant.

Using (equation 32), we add up the value of all new patents at time t, and divide by output,

$$\hat{\chi}_t = Y_t^{-1} \int_{H_{t-1}}^{H_t} \xi_{j,t} \, dj = B X_t^{-1} \int_{H_{t-1}}^{H_t} \theta_j \, dj$$

$$\propto \frac{X_t - X_{t-1}}{X_t}$$

$$(34) \qquad = \frac{\chi_t}{1 + \chi_t}.$$

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

$$(35) \qquad M_t = E_t \left[\sum_{s=t}^{\infty} \beta^{s-t} \frac{U'(C_s)}{U'(C_t)} (Y_s - w_s) \right] = \frac{1}{\rho (1 - \beta)} Y_t.$$

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

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SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

REFERENCES

Abrams, David S., Ufuk Akcigit, and Jillian Popadak, "Patent Value and Citations: Creative Destruction or Strategic Disruption?," NBER Working Paper 19647, 2013.

Acemoglu, Daron, Ufuk Akcigit, Nick Bloom, and Kerr William, "Innovation, Reallocation and Growth," Working paper, Stanford University, 2011.

Aghion, Philippe, and Peter Howitt, "A Model of Growth through Creative Destruction," *Econometrica*, 60 (1992), 323–351

Alexopoulos, Michelle, "Read All about It!! What Happens Following a Technology Shock?," *American Economic Review*, 101 (2011), 1144–1179.

Alexopoulos, Michelle, and Jon Cohen, "Measuring Our Ignorance, One Book at a Time: New Indicators of Technological Change, 1909–1949," *Journal of Monetary Economics*, 56 (2009), 450–470.

———, "Volumes of Evidence: Examining Technical Change in the Last Century through a New Lens," *Canadian Journal of Economics*, 44 (2011), 413–450.

Andersen, Torben G., and Timo Terasvirta, "Realized Volatility," in *Handbook of Financial Time Series*, Thomas Mikosch, Jens-Peter Kreiu, Richard A. Davis and Torben Gustav Andersen, eds. (Berlin: Springer, 2009), 555–575.

Atkeson, Andrew, and Ariel T. Burstein, "Aggregate Implications of Innovation Policy," NBER Working Paper 17493, 2011.

Austin, David H., "An Event-Study Approach to Measuring Innovative Output: The Case of Biotechnology," *American Economic Review*, 83 (1993), 253–258.

Basu, Susanto, John G. Fernald, and Miles S. Kimball, "Are Technology Improvements Contractionary?," *American Economic Review*, 96 (2006), 1418–1448.

Baumol, William J., *The Free-Market Innovation Machine: Analyzing the Growth Miracle of Capitalism* (Princeton, NJ: Princeton University Press, 2002).

Bernstein, Jeffrey I., and M. Ishaq Nadiri, "Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality," *Review of Economic Studies*, 56 (1989), 249–267.

Bird, R. E., K. D. Hardman, J. W. Jacobson, S. Johnson, B. M. Kaufman, S. M. Lee, T. Lee, S. H. Pope, G. S. Riordan, and M. Whitlow, "Single-Chain Antigen-Binding Proteins," *Science*, 242 (1988), 423–426.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, "Identifying Technology Spillovers and Product Market Rivalry," *Econometrica*, 81 (2013), 1347–1393.

Bloom, Nicholas, and John Van Reenen, "Measuring and Explaining Management Practices across Firms and Countries," *Quarterly Journal of Economics*, 122 (2007), 1351–1408.

Caballero, Ricardo J., and Adam B. Jaffe, "How High Are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth," in *NBER Macroeconomics Annual 1993,* vol. 8 (Cambridge, MA: NBER, 1993).

Campbell, J. Y., A. W. C. Lo, and A. C. MacKinlay, *The Econometrics of Financial Markets* (Princeton, NJ: Princeton University Press, 1997).

Carley, Michael, Deepak Hegde, and Alan C. Marco, "What Is the Probability of Receiving a U.S. Patent?," *Yale Journal of Law and Technology*, 17 (2015), article 5.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh, *Job Creation and Destruction* (Cambridge, MA: MIT Press, 1998).

Evans, David S., "Tests of Alternative Theories of Firm Growth," *Journal of Political Economy*, 95 (1987), 657–674.

Field, Alexander J., "The Most Technologically Progressive Decade of the Century," *American Economic Review*, 93 (2003), 1399–1413.

Gali, Jordi, "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?," *American Economic Review*, 89 (1999), 249–271.

Garcia-Macia, Daniel, Chang-Tai Hsieh, and Peter J. Klenow, "How Destructive Is Innovation?," NBER Working Paper No. 22953, 2015.

Giuri, Paola, Myriam Mariani, Stefano Brusoni, Gustavo Crespi, Dominique Francoz, Alfonso Gambardella, Walter Garcia-Fontes, Aldo Geuna, Raul Gonzales, Dietmar Harhoff, and Karin Hoisl, "Inventors and Invention Processes in Europe: Results from the PatVal-EU Survey," *Research Policy*, 36 (2007), 1107–1127.

Griliches, Zvi, "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature*, 28 (1990), 1661–1707.

Grossman, Gene M., and Elhanan Helpman, "Quality Ladders in the Theory of Growth," *Review of Economic Studies*, 58 (1991), 43–61.

Hall, B. H., and R. H. Ziedonis, "The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979–1995," *RAND Journal of Economics*, 32 (2001), 101–128.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, "Market Value and Patent Citations," *RAND Journal of Economics*, 36 (2005), 16–38.

Haltiwanger, John, "Job Creation and Firm Dynamics in the United States," in *Innovation Policy and the Economy,* vol. 12 (Cambridge, MA: NBER, 2012), 17–38.

Harhoff, Dietmar, Francis Narin, F. M. Scherer, and Katrin Vopel, "Citation Frequency and the Value of Patented Inventions," *Review of Economics and Statistics*, 81 (1999), 511–515.

Harhoff, Dietmar, Frederic M. Scherer, and Katrin Vopel, "Exploring the Tail of Patented Invention Value Distributions," CIG Working Papers FS IV 97-27, Wissenschaftszentrum Berlin, Research Unit: Competition and Innovation, 1997.

Henry, Matthew D., and John L. Turner, "The Court of Appeals for the Federal Circuit's Impact on Patent Litigation," *Journal of Legal Studies*, 35 (2006), 85–117.

Hsieh, Chang-Tai, and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124 (2009), 1403–1448.

Imrohoroglu, Ayse, and Selale Tuzel, "Firm Level Productivity, Risk, and Return," *Management Science*, 60 (2014).

Klette, Tor Jakob, and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 112 (2004), 986–1018.

Kortum, Samuel, "Equilibrium R&D and the Patent-R&D Ratio: U.S. Evidence," *American Economic Review*, 83 (1993), 450–457.

Kortum, Samuel, and Josh Lerner, "Stronger Protection or Technological Revolution: What Is Behind the Recent Surge in Patenting?," *Carnegie-Rochester Conference Series on Public Policy*, 48 (1998), 247–304.

Laitner, John, and Dmitriy Stolyarov, "Technological Change and the Stock Market," *American Economic Review*, 93 (2003), 1240–1267.

Lamont, Owen, and Andrea Frazzini, "The Earnings Announcement Premium and Trading Volume," NBER Working Paper 13090, 2007.

Lampe, Ryan, and Petra Moser, "Do Patent Pools Encourage Innovation? Evidence from 20 Industries in the 1930s," Chapter in NBER book *Standards, Patents and Innovations*, 2014.

Lentz, Rasmus, and Dale T. Mortensen, "An Empirical Model of Growth through Product Innovation," *Econometrica*, 76 (2008), 1317–1373.

Moser, Petra, Joerg Ohmstedt, and Paul Rhode, "Patents, Citations, and Inventive Output—Evidence from Hybrid Corn," NBER Working Paper No. w21443, 2011.

Moser, Petra, and Alessandra Voena, "Compulsory Licensing: Evidence from the Trading with the Enemy Act," *American Economic Review*, 102 (2012), 396–427.

Moser, Petra, Alessandra Voena, and Fabian Waldinger, "German-Jewish Emigres and U.S. Invention," NBER Working Paper No. 19962, 2012.

Myers, Stewart C., and Nicholas S. Majluf, "Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have," *Journal of Financial Economics*, 13 (1984), 187–221.

Nicholas, Tom, "Does Innovation Cause Stock Market Runups? Evidence from the Great Crash," *American Economic Review*, 98 (2008), 1370–1396.

Olley, G. Steven, and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64 (1996), 1263–1297.

Pakes, Ariel, "On Patents, R&D, and the Stock Market Rate of Return," *Journal of Political Economy*, 93 (1985), 390–409.

Romer, Paul M., "Endogenous Technological Change," *Journal of Political Economy*, 98 (1990), S71–S102.

Scherer, F. M., "Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions," *American Economic Review*, 55 (1965), 1097–1125.

Scherer, F. M., "The Propensity to Patent," *International Journal of Industrial Organization*, 1 (1983), 107–128.

Shea, John, "What Do Technology Shocks Do?," in *NBER Macroeconomics Annual 1998*, vol. 13 (Cambridge, MA: NBER, 1999), 275–322.

Simon, Herbert A., and Charles P. Bonini, "The Size Distribution of Business Firms," *American Economic Review*, 48 (1958), 607–617.

Smets, Frank, and Raf Wouters, "An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area," *Journal of the European Economic Association*, 1 (2003), 1123–1175.

Smiley, G., *The American Economy in the Twentieth Century* (Mason, OH: South-Western, 1994).

Syverson, Chad, "Product Substitutability and Productivity Dispersion," *Review of Economics and Statistics*, 86 (2004), 534–550.

———, "What Determines Productivity?," *Journal of Economic Literature*, 49 (2011), 326–365.