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Leonid Kogan
Dimitris Papanikolaou
Amit Seru
Noah Stoffman

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ABSTRACT

We explore the role of technological innovation as a source of economic growth by constructing direct measures of innovation at the firm level. We combine patent data for US firms from 1926 to 2010 with the stock market response to news about patents to assess the economic importance of each innovation. Our innovation measure predicts productivity and output at the firm, industry and aggregate level. Furthermore, capital and labor flow away from non-innovating firms towards innovating firms within an industry. There exists a similar, though weaker, pattern across industries. Cross-industry differences in technological innovation are strongly related to subsequent differences in industry output growth.

Leonid Kogan
MIT Sloan School of Management
100 Main Street, E62-636
Cambridge, MA 02142
and NBER
lkogan@mit.edu

Dimitris Papanikolaou
Department of Finance
School of Management
Northwestern University
Office Jacobs 433
2001 Sheridan Road
Evanston, IL 60208
d-papanikolaou@kellogg.northwestern.edu

Amit Seru
Booth School of Business
University of Chicago
5807 South Woodlawn Avenue
Chicago, IL 60637
and NBER
amit.seru@chicagobooth.edu

Noah Stoffman
Kelley School of Business, Indiana University
1309 E 10th Street
Bloomington, IN 47405
nstoffma@indiana.edu

Economists since Schumpeter have argued that technological innovation, combined with resource reallocation, is the engine that sustains long-term economic growth. However, the impact of technical change on economic growth and business cycle fluctuations remains difficult to quantify. Similarly, while technology shocks play a central role in macroeconomic real business cycle models, there is little consensus on whether these shocks represent actual technological improvements, or are reduced-form representations of other economic forces.[1] The primary reason for these ambiguities is the difficulty in measuring technological innovation in the data. This paper aims to fill this gap.

We construct a novel economic measure of innovation that combines information from patent dataset with stock market data over the period 1926 to 2010.[2] Measuring technological innovation through patents offers important advantages. Patents are a direct measure of innovation that are available as far back as the eighteenth century. However, the use of patents as a measure of innovation has one important shortcoming: not all patents are of equal economic value. Thus, an increase in the number of patents granted need not coincide with greater technological innovation. Our central idea is to use the stock market reaction around the day the patent is granted to appropriately weigh each patent. On the day that the patent is granted, market participants learn the full details of the patent. We use this stock market reaction as a measure of patent quality to construct measures of innovation at the firm, industry and economy level which allows us to evaluate the reallocation and growth dynamics within and across industries after bursts of innovative activity.

Our approach to measuring the quality of patents offers distinct advantages over the existing measures of patent quality. Patent citations contain useful information that can be used to assess the quality of patents.[3] However, patent citations suffer from two major drawbacks. First, measuring future citations each patent generates requires information over the entire sample. In many economic applications – such as when exploring the short and medium run response of investment or hiring decisions to innovation – it may be more desirable to use a measure that depends on the contemporary assessment of the value of a patent, as is the case with our measure. Second, the patent citation data is reliably available only in the later part of our sample.[4] This lack of information creates problems in assessing the quality of earlier patents, since patents often tend to cite only the most

[1] See, for instance, Cochrane (1994).

[2] Several new studies exploit the same source of patent data (Google Patents) as we do in our paper. For instance, see Moser and Voena (2011), Moser, Voena, and Waldinger (2012) and Lampe and Moser (2011).

[3] See, for example, Harhoff, Narin, Scherer, and Vopel (1999), Hall, Jaffe, and Trajtenberg (2005) and Moser, Ohmstedt, and Rhode (2011).

[4] Moser and Nicholas (2004) and Nicholas (2008) discuss the difficulty in reliably extracting citations data from patent documents before 1975. Also note that 1947 is the first year citations were officially included on patent documents.

recent ones.[5] In contrast, our measure is reliably available over a long time period allowing us to make meaningful comparisons. Despite these two drawbacks, patent citations do provide an independent measure of the *ex-post* value of a patent. Thus, we use patent citations as a validation of our procedure. We find that the firm's stock market reaction when the patent is granted is a strong predictor of the number of citations the patent receives in the future.

Our measure of technological innovation captures known periods of high technological progress as well as firms driving these waves (e.g., technologically progressive 1960s and early 1970s, see Laitner and Stolyarov (2003)). In addition, the empirical distribution of firm-level innovation measure is extremely fat-tailed, since a few large firms contribute disproportionately to the aggregate rate of innovation in the economy. The identity of these firms varies by decade. This finding is consistent with past research which describes the nature of radical innovations (Harhoff, Scherer, and Vopel (1997)). Furthermore, we find that characteristics of innovating firms using our measure match those of innovators as described by Baumol (2002), Griliches (1990) and Scherer (1983).

Armed with our measure, we examine the relation between innovation and economic growth. First, we explore the link between firm productivity and innovation. Our innovation measure is strongly linked to productivity of capital and labor, both at the firm and at the industry level. Firms and industries that innovate experience a surge in productivity. The innovation activity of competing firms has a negative effect on firm productivity, but only in the short run. The long run response of firm productivity to the innovation activity of other firms in the industry is either zero or positive.

We find several patterns in the data that are consistent with Schumpeter's notion of "creative destruction". Capital and labor are reallocated towards firms that innovate, away from firms that do not. We find similar patterns of reallocation across industries. An increase in the innovation activity of other industries is associated with an increase in the cost of labor, resulting in an outflow of labor if the industry innovates less. The corresponding patterns for capital are similar, but weaker, consistent with the view that labor has lower specificity than capital (Ramey and Shapiro, 2001). In addition, we find that an increase in industry innovation is also associated with an increase in the rate of firm exit.

Our final step is to relate aggregate growth to innovation. To do so, we estimate the impulse response of aggregate total factor productivity (TFP) and output to our aggregate innovation measures. Our innovation measure accounts for a substantial fraction of movements in aggregate

[5]For instance, the telephone patent by Alexander Graham Bell (patent number 174,465) has only one citation in the Google Patent database.

TFP. An increase in innovation is associated with an increase in aggregate output, although with a lag of three to four years. We find similar patterns in the cross-section. Differences in innovation are strongly related to differences in subsequent growth both at the industry and firm level. These findings make a strong case for innovation as a source of long-run firm growth, consistent with the equilibrium model of Klette and Kortum (2004).

Our paper is connected to several strands of the literature. Our work is closely related to the literature in macroeconomics that tries to measure technological innovation. Broadly, there are three three main approaches to identify technology shocks. First, researchers have measured technological change through Solow residuals, after accounting for non-technological effects such as imperfect competition and varying utilization (e.g., Basu, Fernald, and Kimball (2006)). Second, researchers have imposed long-run restrictions on vector auto-regressions (VARs) to identify technology shocks. Both of these approaches measure technology indirectly. The resulting technology series are highly model-dependent, as they depend on the identification assumptions.

Our approach falls into the third category, which constructs direct measures of technological innovation using micro data. 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 assuming that all patents are of equal value. Indeed, Kortum and Lerner (1998) show that there is wide heterogeneity in the economic value of patents. Furthermore, fluctuations in the number of patents granted are often the result of changes in patent regulation, or the quantity of resources available to the US patent office (see e.g. Griliches (1990) and 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.[6] 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 does not directly capture the economic value of innovation. In contrast, our measure is available at the firm level, which allows us to evaluate reallocation and growth dynamics across firms and sectors.

Our paper is not the first to link firm patenting activity and stock market value (Pakes, 1985; Austin, 1993; Hall et al., 2005; Nicholas, 2008). In particular, Pakes (1985) examines the relation

[6]Kortum (1993) documents that the patent-to-R&D ratio has shown a secular decline in the US.

between patents and the stock market rate of return in a sample of 120 firms during 1968–1975. 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 employ to study reallocation and growth dynamics.

Our paper is also related to work that examines whether technological innovation leads to positive knowledge spillovers or business stealing. Closest to our paper is the work of Bloom, Schankerman, and Reenen (2010), 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 stock market reaction and assessing within- as well as between-industry reallocation and growth dynamics after bursts of innovative activity.

Our work is also related to literature on endogenous growth and creative destruction (see Acemoglu (2009) for a textbook treatment). Closest to our work are the papers that explore the impact of innovation on firm productivity and growth (Caballero and Jaffe, 1993; Akcigit and Kerr, 2010; Acemoglu, Akcigit, Bloom, and William, 2011). Finally, our paper is also related to work that explores the micro-foundations of aggregate economic shocks. In particular, Gabaix (2011) proposes that if the distribution of firm size is sufficiently fat-tailed, as is the case in the US and in most of the world, firm-specific shocks can have substantial effects on aggregate quantities due to the failure of the law of large numbers. Consistent with this view, the empirical distribution of firm-level innovation measure is fat-tailed, suggesting that the innovative activity of a few large firms can have a large aggregate impact. However, we find evidence of comovement of our innovation measures across firms, suggesting that common shocks play an important role as well.

The remainder of the paper is organized as follows. In Section 2 we explain the process of constructing our dataset. We describe the constriction of our innovation measure in Section 3. Section 4 studies the response of individual firms and industries on our innovation measure and documents patterns of reallocation. Section 5 explores the response of aggregate variables on our innovation measure. Section 6 discusses the connection of our findings with existing models and concludes.

2 Data

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

2.1 Patent Data

Patents in the United States are granted by the United States Patent and Trademark Office (USPTO). We download the entire history of U.S. patent documents from Google Patents.[7] Each of about 7.8 million patent files was downloaded using an automation script.[8]

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

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

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

Matching patents to firms

Here, we briefly discuss the steps our matching procedure followed, but provide extensive detail in the Online Appendix. We search the document for the words "assignee" or "assigned" and extract the text that immediately follows. This text is either a company name, or the name of an individual to whom the patent was assigned. We then count the number of times each assignee name appears

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

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

across all patent documents. We compare each assignee name to more common names, and if a given name is "close" (in the sense of the Levenshtein distance[9]) to a much more common name, we substitute the common name for the uncommon name. For example, one of the most common names is "General Electric Company", which is associated with over 43,000 patents. We substitute this name for the far less common, but quite similar, names "General Electbic Oohpany", "General Electbic Cqhpany", and "Genebal Electbic Compakt".

At this point, we have an assignee name for each patent. These names must be matched to a company identifier such as the CRSP permco. This is accomplished in two steps. We begin by looking only at patents that are also in the NBER database. For each assignee name identified in the steps above, we count how many different permcos are matched to patents in the NBER database. For example, all of the patents with an assignee name "General Electric Company" are matched to one permco in the NBER database. We can therefore safely assume that *all* of the patents assigned to the General Electric Company can be matched to that permco, *even for patents not included in the NBER data.* Remaining assignee names are matched to CRSP firm names using a name matching algorithm.[10] The algorithm uses a score based on the inverse word frequency to match assignee names to possible company names. For example, the word "American" is quite common in company names, and so contributes little to name matching; the word "Bausch" is quite uncommon, so it is given much more weight. Visual inspection of the matched names confirms very few mistakes in the matching.

Extracting patent citations

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

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

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

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

Summary statistics

We now provide some statistics that lend credence to our method for extracting patent information. Table 1 shows how many patents we match to companies. Of the 6.0 million patents granted in or after 1926, we find the presence of an assignee in 2.8 million. The matching procedure provides us with a database of 1.8 million matched patents, of which 435,814 (24%) are not included in the NBER data. Figure 1 graphs the total number of patents matched by the year the patent was granted. Patents included in the NBER data, which is the most comprehensive database previously available, are shown in light shading. Patents unique to our database are presented in dark shading. Note that the two sets of data appear to fit together fairly smoothly, and that even during the period covered by the NBER data, our database adds an average of 2,187 patents to the NBER data.[11]

Table 2 provides additional summary statistics. Overall, our data provides a matched permco for 66% of all patents with an assignee, or 31% of all granted patents. By comparison, the NBER patent project provides a match for 32% of all patents from 1976–2006, so our matching technique works quite well, even using only data extracted from OCR documents for the period before the NBER data. Another point of comparison is Nicholas (2008), who uses hand-collected patent data covering 1910 to 1939. From 1926–1929, he matches 9,707 patents, while our database includes 8,858 patents; from 1930–1939 he has 32,778 patents while our database includes 47,039 matches during this period.

2.2 Stock Market and Financial Data

The return data used to assess the stock market response to news about patents are from CRSP over the period 1926–2010. In several of our analyses we use financial and accounting data that are from Compustat. The sample in these cases is determined by the availability of Compustat data (available from 1951 onwards). As is standard, we omit financial firms and utilities from our analysis. See appendix A for variable definitions.

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

3 Measuring innovation

In this section we explain how we construct our firm, industry and aggregate level measures of innovation. Our innovation in this paper is to identify the value of a patent from the stock price reaction around the days that the market learns that a firm has applied for a specific patent, or that a patent has been granted to the firm.

In order to examine stock market reactions, we need to define what constitutes an information event. Prior to 2000, patent application filings were not publicized (see e.g. Austin (1993)). In contrast, information does become widely available when patents are granted. The USPTO's publication, *Official Gazette*, which is published every Tuesday, lists patents that are granted that day and reports details of the patent. Subsequent to the American Inventors Protection Act of 1999, the USPTO also began publishing applications 18 months after filing even if the patents had not yet been granted. Publication of these applications occurs on Thursday of each week. When application publication dates are available, we combine the stock market reaction around both information events to construct our innovation measure.

When constructing our innovation measure, we only use information on patents by publicly-traded firms. Hence, one worry is that we do not include private companies, several of which might be responsible for large and more important productivity shocks.[12] This omission is likely to bias our findings toward zero. The magnitude of any bias, however, is likely to be small. First, Bloom et al. (2010) show that public firms in Compustat account for most of the R&D expenditures in the United States. Second, Baumol (2002) notes that while several independent and private firms might provide initial innovation, large publicly traded firms conduct most of the refinements that lead to large improvements in welfare.

We should stress that while our method identifies the value of a patent, relying on stock market reaction suffers from two limitations. First, market participants may have advance knowledge of the patent, either through information leakages, or because the firm has chosen to make its patent application public. If so, the stock market reaction on the patent grant day or publication date would underestimate the economic value of the patent. Second, our method only allows us to measure the private value of the patent. In contrast, the social value of a patent can be higher, or lower, depending on whether the patent generates research spillovers or steals business from existing firms. Notably, the challenge of accurately measuring the private and social value of an innovation

[12]Kortum and Lerner (2000) find that venture capital, which accounts for 3% of total R%D expenditures, is responsible of 15% of industrial innovations.

is not unique to our paper, but confronts other measures, such as R&D or patent citation counts, as well.

3.1 Extracting patent value from stock price reaction

We extract information about the value of each patent from stock price reactions using two methods: a simple measure that ignores measurement error, and a more sophisticated measure that incorporates the error into the estimation procedure.

A simple measure

To isolate market movements we focus on the firm's idiosyncratic return, r_{ft}, defined as the firm's return minus the return on the market portfolio. 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. Unless noted otherwise, our results are quantitatively similar when using this alternative definition.

Given our measure of idiosyncratic firm return, we construct the idiosyncratic stock price reaction as the firm's idiosyncratic return during the announcement window, r^l_{jd}, times the market capitalization of the firm, S_{jd-1}, on the previous day:

$$A_j = r^l_{jd}\, S_{jd-1}, \qquad r^l_{fd} \equiv \sum_{t=0}^{l} r_{jd,d+t}. \tag{1}$$

The next step is to choose the length of the announcement window, l. As we show below, trading volume is higher on the two days following a patent being granted, suggesting that the stock price movements in days after the announcement are also informative. The downside is that increasing the announcement window can potentially add noise to our estimates. In the baseline case, we choose a three-day window ($l = 2$). As a robustness test, we extend the window to five days ($l = 4$).

The private value of a patent is generally nonnegative because a firm can always choose not to implement it. Therefore, when we construct our innovation measure, we restrict attention only to positive stock price responses:

$$A^+_j = \max[A_j, 0]. \tag{2}$$

Our first measure of innovation A_j^+ is easy to construct, since it involves no estimation of parameters. The downside, however, is that it ignores the possibility of measurement errors. In particular, by truncating returns at zero we are introducing an upward bias in our estimate of the dollar value of innovation. The magnitude of this bias is increasing in the volatility of the firm's idiosyncratic return. To ensure that the variation in our measure A_j^+ does not result from variation in the firm volatility, we control for idiosyncratic volatility σ_{ft} throughout.

Adjusting for measurement error

We construct an alternative measure of innovation to explicitly account for measurement error introduced while constructing the simple measure.[13] In other words, we account for that fact that the stock price of innovating firms may fluctuate for reasons unrelated to innovation during the announcement window. The idiosyncratic stock return during the announcement day window can be decomposed as:

$$r_{jd}^l = x_j + e_{jdl}, \tag{3}$$

where x denotes the value of the patent (as percentage of market value) and e_{dl} the component of firm stock return that is unrelated to the patent. Under the assumption that $e_{jdl} \sim \mathcal{N}(0, \xi_j)$ and x is distributed according to a Gaussian $\mathcal{N}(0, v_j)$ truncated at zero, we can construct the conditional expectation of the value of the patent as a function of the firm's stock return:

$$E[x_j | r_{jd}^l] = \delta_j \, r_{jd}^l + \sqrt{\delta_j \, \xi_j} \, \frac{\phi(R_j)}{1 - \Phi(R_j)}, \tag{4}$$

where ϕ and Φ are the standard normal pdf and cdf, respectively, and

$$R_j = -\sqrt{\delta_j} \, \frac{r_{jd}^l}{\sqrt{\xi_j}}, \qquad \delta_j = \frac{v_j}{v_j + \xi_j}. \tag{5}$$

In order to operationalize our procedure, we need estimates of v_j and ξ_j, preferably at the firm level. To reduce the number of parameters, we assume that $\delta_j = \delta$, that is, the signal-to-noise ratio is constant across firms and time. To estimate δ, we regress log squared returns on a patent announcement-day dummy variable, I_{fd},

$$\ln \left(r_{fd}^l \right)^2 = a_0 + a_{ft} + b_d + \gamma I_{fd} + u_{fd}, \tag{6}$$

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

controlling for firm-year (a_{ft}) and day-of-the-week (b_d) fixed effects. The signal-to-noise estimate is then:

$$\hat{\delta} = 1 - \frac{var(r^l_{fd}|I_{fd}=0)}{var(r^l_{fd}|I_{fd}=1)} = 1 - e^{-\hat{\gamma}}. \tag{7}$$

We estimate (6) using a three-day ($l = 2$) and a five-day ($l = 4$) return announcement window. We obtain estimates $\hat{\delta} \approx 0.031$ in both cases, so we use this as our benchmark value.

Next, we estimate the measurement error ξ_j. There is strong evidence that firm-volatility varies both in the time-series and the cross-section, hence it is important to allow ξ_j to vary both across firms and time. For every firm f and year t we estimate its idiosyncratic variance, σ^2_{ft}, from daily returns. This variance is estimated over both announcement and non-announcement days, so it is a mongrel of both v and ξ. Given the estimate of the daily variance σ^2, the fraction of trading days that are announcement days, μ, and our estimate for the signal-to-noise ratio, $\hat{\delta}$, we recover the measurement error by $\xi_{ft} = \sigma^2_{ft}\,(1+l)\,\left(1+\mu_{ft}(1+l)\frac{\hat{\delta}}{1-\hat{\delta}}\right)^{-1}$.

We then construct our second innovation measure as:

$$\hat{A}_j = E[x_j|r^l_{jd}] \times S_{jd-1}. \tag{8}$$

Our second innovation measure (8) explicitly accounts for the fact that a firm's idiosyncratic return may contain information unrelated to the value of a patent. The conditional value of a patent in equation (4) is an increasing and convex function of the daily firm return, and thus has a similar shape as our simple innovation measure (2), up to a scale parameter that depends the the signal to noise ratio.

3.2 Information in stock-price responses

We now provide evidence that the stock market reaction contains valuable information about the value of a patent. First, we document that trading volume increases around the days that patents are granted (or their applications are published).[14] Second, we document that the stock market reaction of a patent is correlated with an independent measure of its *ex-post* value–the number of future citations the patent receives.

[14]Though prices can adjust to new information absent any trading, the fact that stock turnover increases following a patent grant or publication is consistent with the view that some information is released to the market, and not all agents share the same beliefs.

Trading volume

We regress a firm's turnover x (trading volume divided by shares outstanding) on an announcement day dummy variable I_{fd},

$$x_{fd+k} = a_0 + a_{ft} + b_d + b(k)\, I_{fd} + u_{fd}, \tag{9}$$

controlling for firm-year ζ_{ft} and day of the week b_d fixed effects. We vary k from -1 to 5.

Table 3 shows the results of estimating equation (9). We find that there is a statistically significant increase in share turnover around the day that the firm is granted a patent (Panel A) or its application is publicized (Panel B). Volume increases on the day of the announcement, and remains temporarily higher for the next couple of days. We find that the total turnover in the first three days after the announcement increases by 0.21-0.40%. Given that the daily median turnover rate is 1.29%, this is an economically significant increase in trading volume, consistent with the view that patent issuance conveys important information to the market.

Patent citations

The next step is to explore whether the stock price reaction around the day of the announcement carries information about the likelihood of the patent receiving citations in the future. We look at patent citations because they represent an independent measure of the *ex post* value of a patent.

We examine whether the firm's stock price reaction when granted patent j is correlated with the number of future citations, C_j, the patent subsequently receives:

$$C_j = a + b\, A_j + \gamma_y + \gamma\, \log \sigma_j + e_j. \tag{10}$$

We include grant-year (or publication-year) fixed effects (γ_y) in the regression because older patents have had more time to accumulate citations. We include the firm's idiosyncratic volatility σ to control for the truncation-induced bias in our simple measure measure A^+. We consider both three-day ($l = 2$) and five-day ($l = 4$) announcement day windows. We cluster the standard errors by year.

We show the estimation results in Table 5. Our truncated measure A^+ is informative about the number of future citations. As we see in Panel A, the coefficient of patent citations on our innovation measure is statistically significant across patent length windows. The economic magnitudes are moderately significant. The median number of citations a patent receives is 5. An increase from the median to the 90th percentile in terms of stock price reaction around the day the patent is

granted (its application is publicized) is associated with 0.3 (0.2) more citations. The magnitudes are substantially larger when we use our measure adjusted for measurement error, as we see in Panel B. An increase from the median to the 90th percentile in terms of our innovation measure $\hat{A}$ is associated with 1.6-1.8 (0.4-0.5) more citations, measured around the patent grant (publication) day.[15]

Next, we repeat the exercise, replacing A_j with its logarithm, $\ln A_j$. This serves two purposes. First, it ameliorates the effects of outliers. Second, for our truncated measure A^+, it explores whether the positive effect on citations comes from the transition from zero to positive, or does it also exist if we focus on the positive responses alone. As we see in Panels C and D, the semilog specification yields estimates that are economically more significant. An increase in A^+ and $\hat{A}$ from the median to the 90th percentile is associated with 1.8-2.1 (0.7) more patent citations, using data on patent grant (publication) day.

In addition, we perform a number of robustness tests, the results of which are available in the Online Appendix. First, our findings are quantitatively similar if we estimate equation (10) with a Poisson or negative binomial regression. Second, the results using our second idiosyncratic return measure (the firm's return minus the beta-matched portfolio) are similar, though one-third smaller in magnitude. Third, we explore what happens if we do not truncate the idiosyncratic dollar return A_j. We find that the simple non-truncated dollar return A_j is essentially uncorrelated with future citations.

The results of this section suggest that the stock price reaction within a few days after the patent is granted contains important information about the value of the patent. We use this information to weigh the number of patents when we construct measures of innovation at the firm, industry or aggregate level. Since the point estimates are a bit higher when we use a three-day versus a five-day window, we focus on the former throughout the paper. Finally, the stock price reaction around both the grant as well as the publication date appear to be informative. Thus, in what follows, we measure the value of each patent as the sum of the values obtained using the grant-day and publication-day windows.

3.3 Some illustrative case-studies

Before turning to our main results, we provide some illustrative case studies to highlight the success of our method in identifying valuable patents. For these examples we performed an extensive search

[15]Note that small changes in citations generated by a patent (around the median number) can be associated with large value implications for the firm producing the patent (Hall et al. (2005)).

of online and print news sources to confirm that no other news events could 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. As shown in panel A of Figure 2, the stock price increased 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, Hardman, Jacobson, Johnson, Kaufman, Lee, Lee, Pope, Riordan, and Whitlow (1988), was published in *Science* and has since been cited over 1300 times,[16] while the patent itself has been 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, which was granted to Protein Design Labs on December 17, 1996. The stock rose 22% in the next two days on especially high trading volume (Panel B of Figure 2). 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."

Finally, 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 rose 34% in the two days after the announcement, adding $900 million in market capitalization (see panel C of Figure 2).

Other patents associated with large returns include an ink jet technology granted to Canon in 1982 (panel D of Figure 2), and a digital storage device granted to Sperry Rand in 1959. These

[16] Google Scholar citation count.

examples, and a number of others we carefully investigated indicate that our method of identifying important patents by looking at stock returns appears to work well.

3.4 Construction of innovation measures

We now explain how we use the stock price reaction of innovating firms to construct measures of innovation at the firm, industry and aggregate level. In addition, we discuss various properties of our measures, which together, strongly reaffirm that these measures are reasonable indicators of innovative activity.

Firm-level measures of innovation

In most of our analysis, the unit of observation is a year because of the availability of macroeconomic data. Hence, we need to construct measures of innovation at annual frequencies. We do so by summing over the stock price reaction across all patents granted, or its application published, to firm f in year t,

$$A^v_{ft} = \sum_{j \in J^g_{ft}} A_j + \sum_{j \in J^p_{ft}} A_j, \qquad A_j \in [A^+_j, \hat{A}_j], \tag{11}$$

where J^g_{ft} and J^p_{ft} denote the sets of patents granted and published applications, respectively, to firm f in year t.

In our firm-level analysis, we scale the dollar value of innovation by the end of year market capitalization, S, in year t:

$$A_{ft} = \frac{A^v_{ft}}{S_{ft}}. \tag{12}$$

Hence, our firm-level innovation measures can be interpreted as the fraction of firm f's value that can be attributed to innovation in year t. (Replacing market values in the denominator by lagged market values gives very similar results.)

Table 4 presents some descriptive statistics for our measure. As we see, the distribution of our firm-level measure is rightly skewed, as roughly two-third of the firms do not innovate. Furthermore, the distribution of our firm-level measures of innovation A^+_f and $\hat{A}_f$ has fat tails. In Figure 3 we plot the log complementary empirical cdf, $\log(1 - F(A))$, versus the log innovation measure, $\log A$, for the top 10 percent of the distribution. The relation is close to linear, with a slope coefficient of approximately -1.9. Hence, the tail behavior of A can be well approximated by a power law. A simple estimator of a power law exponent (see e.g. Newman (2005)) yields a point estimate of

-2.75.[17] Our findings are consistent with Harhoff et al. (1997), who show that the distribution of patent citations has fat tails.

In addition to some patents being very valuable, our results indicate that a few large firms are very important for the aggregate rate of innovation in the economy. The identity of these firms varies by decade. In the 1930s and 1940s, AT&T and GM are responsible for a large share of innovative activity. In the 1950s and 1960s, du Pont and Kodak take a leading role. In 1970s and 1980s, a large share of innovation takes place in Exxon, GE, 3M and IBM. Finally, in the 1990s and 2000s, "new economy" firms are responsible for a large share of innovation, namely Sun, Oracle, Microsoft, Intel, Cisco, Dell, and Apple.

Next, we explore how our firm-level measures of innovation are related to firm characteristics, in particular Tobin's Q, firm size, K, and R&D spending (normalized by assets):

$$A_{ft} = a_0 + a_1 \log Q_{t-1} + a_2 \log K_{t-1} + a_3 \log RD_{t-1} + \rho\, A_{ft-1} + u_{it}. \tag{13}$$

We estimate equation 13 using the entire sample of Compustat firms from 1950 to 2010 using a Tobit model.[18] We include industry dummies to account for industry-level time invariant characteristics; and time dummies to account for changing state of the business cycle as well as changes in patent law or changes in the efficiency and resources of the USPTO (see e.g. Griliches (1989)) during our sample period. We cluster the errors by firm.

We show the results in Table 6. We find that firms that are large, have higher Tobin's Q, and have higher R&D expenditures are more likely to innovate. These findings are similar to those discussed in Baumol (2002), Griliches (1990), Scherer (1965) and Scherer (1983) on the characteristics of firms that have conducted radical innovation and have been responsible for technical change in the U.S.

Aggregate measures of innovation

We construct industry-level and economy-wide measures of innovation by aggregating our firm-level measures across firms. In particular, we construct dollar measures of innovation, by summing up the firm-level measures across the set N_t of firms in the economy or at the industry:

$$A^v_t = \sum_{f \in N_t} A^v_{ft}, \qquad A^v_{ft} \in [A^{+v}_{ft}, \hat{A}^v_{ft}]. \tag{14}$$

[17] This estimator assumes that A is i.i.d. across firms and across time. After removing firm and time dummies, the point estimate of the power law exponent is equal to -3.70 and -3.55 for A^+ and $\hat{A}$ respectively.

[18] Note that information on R&D expenditure is reliably reported in Compustat only from 1975 onwards. As a result our sample period for regressions that use R&D stock is restricted to 1975–2010.

Our dollar measure A^v will be mechanically affected by economic forces that affect the level of stock prices but are likely to be unrelated to innovation, such as changes in discount rates. Hence, as before, we scale our dollar measure A^v by the total market capitalization

$$A_t = \frac{A_t^v}{S_t}, \tag{15}$$

where $S_t = \sum_{f \in N_t} S_{ft}$. Thus, our aggregate measure, A_t, is a value-weighted average of our firm-level innovation measure, A_{ft}.

We compare our two measures of aggregate innovation with three aggregate measures proposed in the literature: the log number of total patents granted; the log stock of R&D capital from the BEA; and the log number of technology books published from Alexopoulos (2011). Some of these measures show a secular time trend, so we remove a deterministic time-trend from all measures.

We plot these series in Figure 4. Our measures of innovative activity line up well with the three major waves of technological innovation in the U.S. First, our measures suggest high values of technological innovation in the 1930s.[19] When we dissect our measures we find that firms that primarily contribute to technological developments during the thirties are in the automobiles (such as General Motors) and telecommunication (such as AT&T) sectors. This description fits well with studies that have examined what sectors and firms led to technological developments and progress in the 1930s (see Smiley (1994)).

Second, our measures suggest higher innovative activity during 1960s and early 1970s – again a period commonly recognized as a period of high innovation in the U.S (see Laitner and Stolyarov (2003)). As has been noted, 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 has 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. We next turn to providing firm level evidence that lends additional support to validity of our measures.

[19] Field (2003) refers to this period as the "most technologically progressive decade of the century."

Comparing our aggregate innovation series, we also note four important points. First, our two aggregate innovation series are very similar to each other, suggesting that the truncation bias in A^+ is diversified across firms. Second, our measure displays different behavior than the total number of patents, especially in the beginning and in the end of the sample. The correlation between $\log A^+$ ($\hat{A}$) and the log number of patents is equal to 0.36 (0.42) in levels and 0.16 (0.11) in first differences. Third, our two innovation measures capture similar low-frequency movements to R&D spending and the number of technology books published in the Library of Congress, in particular the rise in innovative activity during the 1960s and early 1970s. Finally, our innovation measures displays substantial high-frequency variability relative to either the stock of R&D or the number of technology books. Some of this variability comes from variation in the number of patents granted, but a significant part comes from changes in the average response of the stock market on these patent grant dates. In contrast, the stock of R&D capital and the number of technology books display mostly low-frequency variation.

We end this section by discussing the drivers of time-series variation in our economy-wide innovation measure. One possibility, in the spirit of the 'granularity' hypothesis of Gabaix (2011), is that the observed time-series variation in aggregate innovation is the result of disproportionately large idiosyncratic shocks that fail to be diversified away. This view is consistent with our findings above that the right tail of our firm-level innovation measure follows a power law. The alternative hypothesis is that there is an underlying macroeconomic shock that affects the firm-level propensity to innovate and the distribution of patent outcomes.

To shed some light on this, we decompose the aggregate measure of innovation A_t^v into A_t^{v1}, the dollar value of innovation that is contributed by the top 1% of firms; and A_t^{v99}, the value that is contributed by the remaining firms. Indeed, our aggregate innovation measure is dominated by a few large firms. Focusing on the sample of firms with positive innovation A_{ft}^v, the top 1% of firms in terms of innovation account for an average of 32% of the total dollar value of innovation A_t^v. If aggregate innovation is determined by large idiosyncratic shocks, we would expect innovations in A_t^{v1} to be uncorrelated with A_t^{99}. Instead, we find that the sample correlation between $\Delta \ln A_t^{v1}$ and $\Delta \ln A_t^{v99}$ ranges from 75% to 78%, depending on our measure. Thus, the data suggests that a systematic shock affecting all firms is responsible for a large portion of the time-series variation in A^v.

4 Innovation, productivity and reallocation

Given an economy's stock of productive inputs, to maximize the economy's overall level of production, resources need to be allocated to the most productive firms and industries.[20] Here, we explore this mechanism in more detail on two broad fronts. First, we document the link between innovation and productivity. Second, we show that, consistent with economic optimization, productive resources flow into the innovating firm away from firms that do not innovate. In both of these cases we perform our analysis within as well as across industries.

4.1 Firm-level evidence

We begin by exploring the productivity and reallocation dynamics subsequent to innovative activity within an industry. In particular, we examine the response of productivity, Tobin's Q and factor demand to a firm's own innovation activity, A_f, and also to the innovation output of its competitors. We construct our measure of innovation of a firm's competitors, A_{If} as the average innovative activity of all firms in the same industry excluding firm f, weighted by market capitalization S:

$$A_{Ift} = \sum_{h \neq f \in N_{It}} A^v_{ht} \Big/ \sum_{h \neq f \in N_{It}} S_{ht}. \tag{16}$$

We define industries using 3-digit SIC codes.[21] We explore the effect of innovation of a firm and its competitors on various firm outcome variables, x, by estimating the regression

$$x_{ft+1} = a_0 + a_1\, A_{ft} + a_2\, A_{Ift} + b\, Z_{ft} + \gamma_t + c_I + \rho\, x_{ft} + u_{ft+1}. \tag{17}$$

We include lags of the dependent variable, industry c_I and year γ_t dummies, and a vector of controls Z. We control for firm idiosyncratic volatility, σ_{ft}, when using our truncated measure A^+ because the magnitude of the truncation bias increases with volatility. We control for firm size, measured as either physical capital or number of employees, because large firms innovate more. In addition, one source of concern is that unobservable variables at the firm or industry level jointly drive innovation outcomes and the outcome variable x. Thus, depending on the specification, we control for firm productivity, profitability, Tobin's Q, and firm and industry stock returns. We present results with and without these controls, and cluster the standard errors by firm.

[20] There exists a large literature on the importance of resource allocation for economic growth (see, e.g. Restuccia and Rogerson (2008); Hsieh and Klenow (2009); Jones (2011); Acemoglu et al. (2011)).

[21] We obtain quantitatively similar results when we define industries according to their 4-digit SIC.

We are interested in the estimates of a_1 and a_2, which capture the impact of innovation by the firm and its competitors. A firm's innovative output, A_f, is highly skewed so we focus on inter-decile movements in firm-level innovation to explore the economic magnitude of a_1. In addition, the innovation of other firms can have a positive or a negative effect on a firm's outcome variables. An increase in the innovative output of competing firms can have a positive effect on the firm because of knowledge spill-overs. However, innovation of competitors can also have a negative effect due to business stealing or an increase in factor prices. We should note that the presence of unobserved variables (the "reflection problem") leads to an upward bias in the estimate of externalities, a_2 (e.g., see Bloom et al. (2010)). For instance, common productivity shocks could impact many firms in the same industry – thereby creating a positive correlation between innovative activity of a firm's competitors and a firm's own productivity.

Productivity

First, we examine whether firms that innovate have higher productivity subsequent to innovative activity. We consider both capital- and labor-productivity (mpk_{ft} and mpl_{ft}), defined as firm output—total sales plus change in inventories—divided by capital and number of employees, respectively. We evaluate the relation between subsequent productivity of capital and labor and innovation by a firm or its competitors by estimating (17) with $x_{ft} = [\log mpk_{ft}, \log mpl_{ft}]$. Depending on whether we focus on the productivity of capital or labor, we measure firm size as the stock of physical capital or number of employees respectively.

We report the results in Panel A of Table 7. We find a substantial increase in firm-level productivity subsequent to an innovation. Our estimates of a_1 imply that an increase in innovation by the firm from the 50th to the 90th percentile leads to an 0.6% to 1.5% increase in the productivity of capital and a 1.7% to 2.1% increase in the productivity of labor. Furthermore, we find some evidence that the business-stealing effect dominates, as the estimated coefficient a_2 are negative and statistically significant. In particular, a one-standard deviation increase in the amount of innovation by the firm's competitors is associated with a 1.5% to 1.9% decline in the productivity of capital and a 1.5-1.8% decline in the productivity of labor. Our finding that labor productivity increases following innovation, suggests that during our sample period, innovation is more likely to be labor augmenting than labor saving on average (see, e.g. Acemoglu (2010)).

Our estimates imply that the business-stealing effect is substantial. However, this finding may be an artifact of the short-horizon considered in our analysis if the business-stealing effect and

positive spillovers operate at different frequencies. In particular, positive spillovers may affect firms with a lag, so in the medium-run, the response of productivity may be different. To explore this possibility, we estimate a dynamic version of equation (17) with k-year ahead productivity, x_{ft+k}, as the regressand. We consider horizons of one to five years $k = [1..5]$. To conserve space, we present results with only size, lagged productivity and volatility controls. Including additional controls leads to quantitatively similar findings.

As we see in Figure 5, the negative effect of competitor innovation, A_{If}, on productivity exists only in the short run. As we increase the horizon k, the estimated coefficients $a_2(k)$ increase, becoming zero or positive after 5 years. In contrast, the positive effect of firm innovation on productivity increases with the horizon k. After 5 years, the response of productivity of capital is between 37% to 50% higher than on impact. Labor productivity displays a similar, though quantitatively stronger response. The positive effect of firm innovation on labor productivity increases with the horizon by 65 percent.

In summary, our findings are consistent with the view that positive spillovers and business stealing operate at different horizons. In the short-run, firms that do not innovate when their competitors do experience a drop in their productivity as they fall behind. However, in the medium run, the innovation of other competitors has either a zero or a positive effect. This positive effect can arise because competitor innovations benefits the firm either directly, for instance through knowledge spillovers, or indirectly, by spurring future firm innovation.

Tobin's Q

Next, we explore the effect of innovation on the market value of the firm. In particular, the firm's Tobin's Q should respond positively to a firm's innovation output. The response of Q to the innovation of the firm's competitors will depend on whether the business-stealing or positive spillover effects dominate in terms of market value. We estimate equation (17) with $x_{ft} = [\log Q_{ft}]$ and present the results in Panel B of Table 7.

We find that Tobin's Q responds positively to a firm's own innovation activity. Our estimates of a_1 imply that an increase in innovation by the firm from the 50th to the 90th percentile leads to an 1.5% to 1.6% increase in the firm's Tobin's Q. These magnitudes are in line with those reported in Hall et al. (2005). In addition, we find some evidence of positive spillovers. A one standard deviation increase in the innovation activity of other firms in the industry is associated with a 0.5% to 0.7% increase in Tobin's Q. However, we must be careful when interpreting this as evidence of

positive spillovers, given the fact that the coefficient a_2 is likely to be biased upwards due to the previously-noted reflection problem.

Our findings here confirm that a firm's innovative activity has an unambiguous positive effect on the firm's productivity and valuation. Our results regarding the net effect of competitor innovation on firm value are less conclusive – an issue we plan to revisit in future work.

Reallocation

In this section we explore the reallocation dynamics subsequent to innovation by a firm. In particular, we explore how our innovation measures are related to reallocation of physical capital and labor. We focus on the firm's investment and hiring rate. In addition, since adjusting a firm's capital and labor input often involves upfront costs, we explore the allocation of financial resources. We focus on the net financial inflows to the firm, defined as new issuance of equity and debt minus payouts to stock- and bond-holders.

We estimate equation (17), using firm investment, i, net hiring rate, h, and financial inflows, e, as outcome variables $x_{ft} = [i_{ft}, h_{ft}, e_{ft}]$. As before, our main estimates of interest are a_1 and a_2, which capture the change in factor inputs and financial inflows following innovation by the firm and its competitors, respectively.

We first examine how physical capital gets reallocated subsequent to innovation by a firm or by its competitors. Table 8 shows that subsequent to an innovation by a firm, there is a substantial increase in its investment rate. In particular, our estimates imply that an increase in innovation by the firm from the 50th to the 90th percentile leads to an increase in the firm's investment rate by 0.5% to 1%. This increase is statistically but also economically significant given that the median firm investment rate is 12% in our sample. Furthermore, we find evidence that physical capital flows from firms that do not innovate to firms that do. If the firm does not innovate but is competitors do, then its investment rate is substantially lower. A one-standard deviation increase in the level of innovation by the firm's competitors leads to a drop in the firm's investment rate by 0.6-1.6%.

Next, we examine reallocation of labor subsequent to innovation by a firm. Table 9 shows that subsequent to an innovation by a firm, there is a substantial increase in its employment using either innovation measure. As before, the economic magnitudes are significant. Our estimates imply that an increase in innovation by the firm from the 50th to the 90th percentile leads to increase in employment of the firm by 0.2% to 0.5%, compared to the median firm-level hiring rate of 2.7%. In addition, labor declines when a firm does not innovate but its competitors in the same industry do.

A one-standard deviation increase in the average innovation of the firm's competitors leads to a reduction of 0.7% to 1.4% in the firm's hiring rate. Our finding that innovating firms increase their labor demand suggests that innovation is more likely to be labor augmenting, and is consistent with the findings of Lentz and Mortensen (2008) for Danish firms.

Last, we examine the reallocation of financial capital subsequent to innovation by a firm and present the results in Table 10. Following to an innovation by a firm, there is a substantial increase in its financial capital inflows. Our estimates imply that an increase in innovation by the firm from the 50th to the 90th percentile leads to an increase of capital inflows to book assets of 0.5% to 0.9%, compared to the median level of zero capital flows. We also find that firms are more likely increase payout and decrease new issuance when the firm does not innovate but is competitors do. In particular, a one-standard deviation increase in the average innovation of the firm's competitors leads to a reduction of 0.8% to 1.6% in net financial capital flows to the firm. This negative effect suggests that firms that fail to innovate in an industry where other firms do, have few investment opportunities. As a result, these firms increase payout to investors.

In summary, our results in this section suggest that, consistent with economic optimization, resources are reallocated to innovating firms and away from firms that fail to innovate when their competitors do. In addition, we find that relative to their median value, new hiring exhibits a quantitatively stronger response than capital, both in terms of inflow and outflow. This increased reallocation response of labor relative to firm capital within industries is consistent with the view that capital is more firm-specific than labor.

4.2 Industry-level evidence

So far we have focused on the dynamics of productivity and reallocation within an industry. We now conduct a similar exercise examining the response of productivity and reallocation of inputs at the sector level. To do so, we use the KLEMS industry-level output data provided by Dale Jorgenson. The advantage of this dataset is that it contains information on the quantity and price of capital and labor inputs at the industry level, which allows us to explore the response of factor prices, in addition to quantities, in response to innovation.

We focus on three outcome variables. First, we document the dynamic response of capital and labor productivity, defined as the ratio of the quantity of output to the quantity of capital and labor services, respectively. Second, we focus on the reallocation of inputs, namely the growth rate in the quantity of capital and labor services. Third, we focus on the rate of establishment exit. Last, we

examine the responses of factor prices, in particular the price of capital and labor services used in industry I, scaled by the consumption deflator.

We estimate specifications similar to (17), but at the industry level:

$$x_{It+1} = a_0 + a_1 A_{It} + a_2 A_{MIt} + b Z_t + \gamma_t + \rho x_{It} + u_{It+1}. \tag{18}$$

Here, A_I is our measure of innovation at the firm-level, and A_{MI} is the average level of innovation in the economy, excluding industry I constructed in a manner similar to (16). Depending on the specification, we include a vector of controls, Z, which includes stock return and, in the case of our truncated measure A^+, volatility, as well as lagged values of the dependent variable and time effects γ_t. In the presence of time dummies γ_t, the interpretation of the coefficient a_2 is unclear, so we only include one of the two. We cluster the standard errors by industry.

Productivity

First, we explore the dynamic response of industry productivity to its own innovation A_I and the innovation of the other industries A_{MI}. We are interested in the coefficients a_1 and a_2, which measure the response of productivity to an industry and economy-wide (excluding the given industry) innovation shock respectively. The coefficient a_1 is informative as to whether innovation creates net value or is a zero-sum game that merely affects the distribution of rents within an industry.

We estimate (18) with k-period ahead productivity as the regressand, $x_{ft+1} = [\log mpk_{ft+k}, \log mpl_{ft+k}]$. We consider horizons of one to five years $k = [1..5]$. We plot the results in Figure 6. We show results with only lagged productivity and volatility controls, but results are similar if we also control for stock returns.

We find that both labor and capital productivity increase in response to own industry innovation. A one-standard deviation A_I shock is associated with a 2.5% increase in the productivity of capital and labor, after a period of 5 years. By contrast, capital and labor productivity show no statistically significant response to the innovation activity of other industries.

Reallocation and Creative Destruction

Next, we examine the response of capital and labor to an industry innovation shock, as well as to the innovation of other industries. We estimate equation (18) with the outcome variable equal to the growth rate in the quantity of capital and labor services $x_{It} = [i_{It}, h_{It}]$. As before, the main

estimates of interest in this specification are a_1 and a_2, which capture the change in the quantity or price of factor inputs in response to innovation in the industry and the rest of the economy respectively. We show our results in Panel A of Table 11.

We find that an increase in the amount of industry innovation increases the quantity of capital and labor services in the industry, though in some specifications the effect is not statistically different from zero. As before, we find that the response of labor is greater than the response of capital. An increase in industry innovation is associated with a 0.2% to 0.4% increase in capital services and a 0.3% to 0.7% increase in labor services. These magnitudes are economically significant, given that the median growth in capital and labor services equals 3.1% and 0.7% respectively.

Our results suggest that increases in economy-wide innovation lead to cross-industry reallocation of labor and capital. In particular, a one standard deviation increase in economy-wide reallocation is associated with a 0.5% to 1.0% drop in the growth of capital services and a 1.4% to 2.2% drop in the growth of labor services.

We also examine patterns of firm exit at the industry level. If industry innovation spurs creative destruction, we expect to find a positive relation between the rate of firm exit and the level of industry innovation. In contrast, innovation in other industries should have less of an effect on the decision of firms to exit the industry. We estimate specifications similar to (18), but we replace the outcome variable with the rate of firm exit and examine the response of this variable to own industry innovation A_I and innovation of other industries A_{IM}. We obtain information on establishment exit rates at the industry level from the US Census tables on Business Dynamics Statistics (BDS). Table 12 presents the results.

Industry innovation is accompanied by an increase in creative destruction. The estimated coefficient a_1 is positive and statistically significant across specifications. Innovation accounts for an economically significant fraction of the variation in firm exit rates. A one standard deviation increase in industry innovation is associated with an increase in the firm exit rate by 0.2% to 0.4%, while the unconditional volatility of exit rates is equal to 2.1%. In contrast, economy-wide innovation A_{MI} has no statistically significant effect on firm exit.

Factor prices

Last, we estimate equation (18) with the outcome variable equal to the growth rate of the price of capital and labor services $x_{It} = [\dot{p}_{It}, \dot{w}_{It}]$, using the KLEMS data by Dale Jorgenson. We show our results in Panel B of Table 11.

Our point estimates suggest that the price of capital and labor increase following an increase in economy-wide innovation. The response of the price of labor is highly statistically significant, consistent with the increased mobility of labor. An increase in innovating activity in other industries increases the outside option of workers, leading to an increase in the equilibrium wage. In contrast, the response of the price of capital to economy-wide innovation is mostly not statistically different from zero, even though the point estimates are similar. This lack of statistical significance is consistent with the view that capital has higher specificity than labor (see e.g. (Hamermesh and Pfann, 1996; Hall, 2002)).

In contrast, we find no statistically significant response of the price of capital or labor services on the industry's own innovation shock. This finding is somewhat puzzling, especially since industry innovation raises the productivity of both capital and labor.

4.3 Innovation and long-run growth

The results of the previous two sections imply that innovation is followed by increased productivity of capital and labor, as well as reallocation of resources towards innovating firms. These findings suggest that own innovation should be followed by increased output growth, both at the firm as well as at the industry level. The response of output to innovation by other firms or industries is more ambiguous. It depends whether productivity increases in the long run, as well as whether the patterns of reallocation we document are reversed in the long run. To answer these questions, we estimate specifications at firm and industry level similar to (17) and (18)

$$\log y_{ft+k} = a_0 + a_1 A_{ft} + a_2 A_{Ift} + b Z_{ft} + \rho_1 \log y_{ft} + \rho_2 \log y_{ft-1} + e_{t+k}, \tag{19}$$

$$\log y_{It+k} = a_0 + a_1 A_{It} + a_2 A_{MIt} + b Z_{It} + \rho_1 \log y_{It} + \rho_2 \log y_{It-1} + e_{t+k}. \tag{20}$$

We again examine horizons of $k = 1$ to $k = 5$ years. We control for volatility (in the case of our truncated measure A^+). In the firm-level regression (19), we also include controls for firm size (capital), and industry and time fixed effects. We cluster the standard errors by firm or industry, respectively. We plot the estimated coefficients $a_1(k)$ and $a_2(k)$ in Figure 7, along with 90% confidence intervals.

We find that both firm and industry output displays a statistically significant response to an own-innovation shock. A firm that experiences an innovation shock from the median to the 90th percentile experiences a 1.5% increase in output over a period of 5 years. The response of output is

quantitatively more significant at the industry level. A one standard deviation shock to industry innovation is associated with a 5.0% output growth over a period of 5 years. Furthermore, a positive innovation by other firms, or industries, is associated with a decline in output. Output falls by 2.5% to 3.5% at the firm level, and by 3.5% to 6.8% at the industry level following innovation by other firms or industries respectively.

In summary, innovation is associated with substantial increases in output. The results of this section can also be summarized by examining the relation between industry innovation in the first half of the sample (1960–1982) and subsequent output growth in the second half of the sample (1983–2006). In Figure 8 we plot the industry innovation measure A_I averaged over the first half of the sample (1960–1982) on the X axis and the corresponding output growth of the industry in the second half of the sample (1983–2006) on the Y axis. The correlation between the two series is 41% with a robust t-statistic of 2.6. Industries which experienced high technological innovation in the first half of the sample were also the ones whose growth rate was subsequently higher in the second half of the sample. For example, industries such as Electrical Machinery, Automotive and Communication, which are in the highest quartile of innovation during the first half of the sample, had an annualized growth rate of more than 4% over the second part of the sample. Similar correlation is found for low-innovative industries such as Textile and Utilities.[22]

5 Innovation and Aggregate Dynamics

Our results in the previous section suggest that innovation is an important determinant of industry-level productivity and growth, especially in the medium term. In this section, we analyze the effect of innovation at the level of the U.S. economy.

[22]One source of concern with our analysis could be that the relation between innovation and output growth is driven by spurious omitted variables. To alleviate these concerns we generate exogenous changes in R&D activity across industries by employing the Bloom et al. (2010) instrument for firm level R&D activity. As discussed in Bloom et al. (2010), the firm level tax price of R&D can be decomposed into a component that is relatively exogenous since it is based on solely on federal rules. In unreported tests we use the Bloom et al. (2010) firm level R&D instrument and construct its industry counterpart by taking the average of this tax price across firms in a given industry. We find qualitatively similar results to those reported in the table when we instrument the endogenous innovation variables (A).

5.1 Total Factor Productivity and Output

Impulse Responses

In this section, we examine the extent to which our innovation measures account for medium-run fluctuations in aggregate productivity and output. We start by exploring the relation between measures of innovation and quantities of interest using VARs and VECMs. Then, we explore whether our results are sensitive to the details of the specification or the construction of our innovation measures. We focus on aggregate productivity and output, with productivity measured using utilization-adjusted TFP from Basu et al. (2006) and output measured as the real per capita gross domestic product. Our aggregate innovation measures A^+ and $\hat{A}$ are constructed according to (14) and (15).

We estimate bivariate VARs of the form $Z = [\log X, \log A]'$, where X is our variable of interest and A is our measure of innovation. We include a deterministic trend, following Alexopoulos (2011). When exploring the responses to our truncated innovation measure A^+, we also include the cross-sectional average of idiosyncratic volatility $\bar{\sigma}$ to ensure that our innovation measure does not pick up movements in firm-level volatility. In addition, we also compute responses using a vector-error-correction model (VECM). We select the number of cointegrating relations using the Johansen test, which suggests the presence of one cointegrating relation in all systems. We select the number of lags using the Akaike-Information Criterion, which advocates a lag length of one to two years for each of the systems. We compute standard errors by a bootstrap simulation of 500 samples. We plot the impulse-response functions in Figures 9 and 10, along with 90% confidence intervals. We compute impulse responses by ordering the innovation shock A last, so the technology shock affects the variables of interest only with a lag.

We find that TFP increases by 0.8% to 2% over 8 years following a one-standard deviation increase in innovation output. The forecast error variance attributed to our innovation measures ranges from 17% to 70% at the 8-year horizon, depending on the specification. Our findings are comparable to the results in Alexopoulos (2011), but in contrast to Shea (1999) who uses only information on patents and finds a negative relation.

Aggregate output displays a mild U-shaped response. In the first two years, the response of output to a one-standard deviation shock is negative at 0.5% to 0.8% and statistically significant. However, in the long-run output increases by a substantial amount: a one-standard deviation innovation shock results to a net 1.5% to 4% increase in aggregate output after 8 years. The share of 8-year forecast-error variance attributed to our innovation measures ranges from 7% to 16%.

Last, we explore whether our measure of innovation contains incremental information to stock prices. Following Beaudry and Portier (2006), we include the level of the stock market in our VAR, scaled by the consumption deflator and population.[23] Doing so, also helps us evaluate the extent to which our results are driven by variation in the denominator of A (the stock market capitalization). We order the level of stock prices second, so now $Z_t = [\log(X_t), \log(M_t), \log \sigma_t, \log(A_t)]'$. Our results are qualitatively similar in terms of statistical significance, but the economic magnitudes are smaller. Productivity and output increase by 0.8 and 2.6% respectively at the peak following a one-standard deviation innovation shock. However, the innovation shock subsumes to a large extent the ability of the stock market to predict TFP and output. The response of output to a one-standard deviation shock in $\log M$ is in most cases not statistically significant beyond the one-year horizon. Furthermore, the innovation shock accounts for a greater fraction of the variance of productivity (2.6% to 18.9%) and output (4.0% to 15.7%) relative to the the stock market shock (1.0% to 8.3% and 1.0% to 13.0%, respectively).

Comparison to Patents or R&D expenses

We explore whether our measure of innovation contributes relative to other commonly employed measures of technological innovation: the stock of R&D capital, and the log number of patents. We estimate two bivariate VARs for productivity, output and consumption, with the log number of patents or R&D capital series ordered last. We show the results in Figure 11. The number of patents has some ability to predict an increase in TFP, but the results are quantitatively weaker. A one-standard deviation shock to the log number of patents is associated with a 0.4% increase in TFP, and the patent shock accounts for 13.1% of the forecast error variance. The response of productivity to the stock of R&D capital is not statistically different from zero.

Furthermore, a simple patent count has essentially no ability to predict business cycle variables. The impulse responses of output and consumption are not statistically significant. Using the stock of R&D capital, we obtain qualitatively similar though quantitatively weaker impulse responses. Output drops in the short run by 0.4%. At the eight-year horizon output displays a statistically significant increase of 0.3%. The shock to the R&D capital accounts for 1.7% of the variance forecast error decompositions of output.

[23] We depart from Beaudry and Portier (2006) in that we include the level of the CRSP value-weighted rather the level of the S&P 500 index, since the former includes all stocks traded on the three major exchanges.

Granger causality

If our measure of innovation indeed represents a fundamental shock, then it should not be predictable by output or productivity. In addition, we explore whether our measure of innovation is predictable by other measures of technological growth in the literature, for instance the book-based measures of Alexopoulos (2011) and the stock of R&D capital.

The top panel of Table 13 shows that output and TFP do not Granger-cause either of our measures of innovation. In addition, the middle panel of Table 13 shows that our measures of innovation are distinct from the measures of Alexopoulos (2011), in that neither causes the other. Our measure is somewhat correlated with the number of patents at 32-43%, but not with R&D spending (less than 10%). The bottom panel of Table 13 shows that our measure is not Granger-caused by either the number of patents or R&D spending.

5.2 Consumption

Next, we analyze the impulse response of aggregate consumption to our innovation measures. The response of consumption is informative about whether our innovation measure is an example of an embodied or disembodied shock. If technological innovation is a free factor of production, in that it costlessly affects all firms in the manner of a disembodied shock, we expect that consumption should increase immediately. Agents anticipating an increase in future consumption would like to increase their consumption today. In contrast, if innovation is not free, because for instance it is embodied in new vintages of capital or due to adoption costs, then consumption may only increase in the long run. In the short run, agents will divert resources away from consumption towards adopting new innovations.

We analyze the response of real per capita consumption of non-durables and services using VARs and VECMs, as in Secion 5.1. We plot the impulse-response functions in Figure 12, along with 90% confidence intervals. We find that consumption displays a U-shaped response to innovation. In the first two years consumption displays a statistically significant drop of 0.5% to 0.7%. Subsequently, consumption increases, leading to a 0.2% to 0.5% net increase after 8 years. However, the increase in consumption is not consistently statistically significant across specifications. The innovation shock accounts for 6% to 8% of the forecast-error variance of consumption growth after 8 years.

The short-run drop in consumption is consistent with the delayed response of output in Section 5.1. Innovation affects output with a lag, so the positive response of consumption is necessarily delayed.

However, our finding that consumption drops in the short run, whereas output does not, suggests that the presence of significant adoption costs.

5.3 Innovation and Tobin's Q

We conclude our analysis by examining the relationship between our measures of innovation and Tobin's Q at the aggregate level. The theoretical relation between innovation and Tobin's Q is ambiguous. If innovation represents an increase in TFP that costlessly affects all firms, then standard models will imply that Tobin's Q should rise (see, e.g. Hayashi (1982)). However, it is also possible that innovation renders part of the capital stock obsolete (see e.g. Laitner and Stolyarov (2003)) or a reduction in profits for incumbent firms (e.g. Greenwood and Jovanovic (1999); Hobijn and Jovanovic (2001)). In these cases the relationship between innovation and Tobin's Q is less clear.

We estimate the contemporaneous response of Tobin's Q to our innovation measures

$$\Delta \log Q_t = a + b\,\Delta \log A_t + c\,Z_t + e_t, \tag{21}$$

where the vector of controls includes lagged values of Q, our innovation measure A and in the case of our truncated measure A^+ changes in the cross-sectional average of idiosyncratic volatility, $\Delta \log \sigma$.

We show the results in Panel A of Table 14. We find that our innovation measure is negatively correlated with Tobin's Q. This negative correlation is statistically and economically significant. A one standard deviation increase in innovation is associated with a 8.1% to 12% contemporaneous drop in aggregate Tobin's Q. Our findings echo the stylized facts reported in Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001) and Laitner and Stolyarov (2003), who argue that Tobin's Q was too low in the 1960s and 1970s, despite the technological advances taking place.

One source of concern with this analysis is that our aggregate innovation measure A may be mechanically negatively related to Q due to our choice of scaling by the market capitalization of all firms S. As a robustness test, we scale our aggregate innovation measure by the market capitalization *of innovating firms*, $S_{It} = \sum_{f \in N_t} S_{ft} \times 1_{A_{ft}>0}$. On average, only about a third of firms innovate in our sample. Thus, this alternative normalization ameliorates somewhat the concern that this finding is mechanical. However, as we show in Panel B of Table 14, we obtain similar results using this alternative normalization.

6 Conclusion

We explore the role of technological innovation as a source of economic growth by constructing direct measures of innovation at the firm level. We combine patent data for US firms from 1926 to 2010 with the stock market response to news about patents to identify the economic importance of each innovation. Our measures allow us to uniquely identify the reallocation and growth dynamics within- and across industry after bursts of innovative activity.

We document a strong link between innovation and productivity at the firm and industry level. Furthermore, we find evidence suggesting that innovation is accompanied by "creative destruction" in the form of resource reallocation, both within and between sectors. Resources flow to innovating firms and sectors, away from firms and sectors that do not. There are stronger patterns of reallocation for labor than for capital, consistent with the view that capital is more specific than labor (Ramey and Shapiro, 2001).

Technological innovation has a significant impact on aggregate variables in the medium run. Our innovation measure is strongly related to aggregate movements in TFP. In addition, aggregate output shows a delayed positive response, consistent with the presence of short-term adoption costs. A positive shock to innovation has a U-shaped effect on consumption growth: consumption is lower in the short-run but increases in the long-run. This is consistent with a reallocation of resources away from consumption in the short-run towards the implementation of innovation. Finally, we find that an increase in innovative activity leads to a fall in aggregate Tobin's Q, consistent with the models of Greenwood and Jovanovic (1999) and Laitner and Stolyarov (2003).

Our empirical findings link medium-run macroeconomic fluctuations to a direct measure technological innovation, consistent with the idea of medium-term cycles of Comin and Gertler (2006). Furthermore, our findings make a strong case for innovation as a source of long-run firm growth, consistent with the equilibrium model of Klette and Kortum (2004).

References

Acemoglu, D. (2009). *Introduction to modern economic growth*. Princeton University Press.

Acemoglu, D. (2010). When does labor scarcity encourage innovation? *Journal of Political Economy 118*(6), 1037 – 10.

Acemoglu, D., U. Akcigit, N. Bloom, and K. William (2011). Innovation, reallocation and growth. Working paper, Stanford University.

Akcigit, U. and W. R. Kerr (2010, November). Growth through heterogeneous innovations. NBER Working Papers 16443, National Bureau of Economic Research, Inc.

Alexopoulos, M. (2011). Read all about it!! What happens following a technology shock? *American Economic Review 101*(4), 1144–79.

Austin, D. H. (1993). An event-study approach to measuring innovative output: The case of biotechnology. *American Economic Review 83*(2), 253–58.

Basu, S., J. G. Fernald, and M. S. Kimball (2006). Are technology improvements contractionary? *American Economic Review 96*(5), 1418–1448.

Baumol, W. (2002). *The free-market innovation machine: analyzing the growth miracle of capitalism*. Princeton University Press.

Beaudry, P. and F. Portier (2006). Stock prices, news, and economic fluctuations. *American Economic Review 96*(4), 1293–1307.

Bird, R., K. Hardman, J. Jacobson, S. Johnson, B. Kaufman, S. Lee, T. Lee, S. Pope, G. Riordan, and M. Whitlow (1988). Single-chain antigen-binding proteins. *Science 242*(4877), 423–426.

Bloom, N., M. Schankerman, and J. V. Reenen (2010). Identifying technology spillovers and product market rivalry. Working paper, Stanford University.

Caballero, R. J. and A. B. Jaffe (1993). 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, Volume 8*. National Bureau of Economic Research, Inc.

Campbell, J., A. Lo, and A. MacKinlay (1997). *The econometrics of financial markets*. Princeton University Press.

Cochrane, J. H. (1994, December). Shocks. *Carnegie-Rochester Conference Series on Public Policy 41*(1), 295–364.

Comin, D. and M. Gertler (2006, June). Medium-term business cycles. *American Economic Review 96*(3), 523–551.

Field, A. J. (2003). The most technologically progressive decade of the century. *American Economic Review 93*(4), 1399–1413.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica 79*, 733–772.

Greenwood, J. and B. Jovanovic (1999). The information-technology revolution and the stock market. *American Economic Review 89*(2).

Griliches, Z. (1989). Patents: Recent trends and puzzles. *Brookings Papers on Economic Activity. Microeconomics*, 291–330.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature 28*(4), 1661–1707.

Hall, B. and R. Ziedonis (2001). The patent paradox revisited: An empirical study of patenting in the u.s. semiconductor industry, 1979-1995. *The RAND Journal of Economics 32*(1), 101–128.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2005). Market value and patent citations. *The RAND Journal of Economics 36*(1), pp. 16–38.

Hall, R. E. (2002, March). Industry dynamics with adjustment costs. NBER Working Papers 8849, National Bureau of Economic Research, Inc.

Hamermesh, D. S. and G. A. Pfann (1996). Adjustment costs in factor demand. *Journal of Economic Literature 34*(3), pp. 1264–1292.

Harhoff, D., F. Narin, F. M. Scherer, and K. Vopel (1999). Citation frequency and the value of patented inventions. *The Review of Economics and Statistics 81*(3), 511–515.

Harhoff, D., F. M. Scherer, and K. Vopel (1997). Exploring the tail of patented invention value distributions. Technical report.

Hayashi, F. (1982). Tobin's marginal Q and average Q: A neoclassical interpretation. *Econometrica 50*(1), pp. 213–224.

Hobijn, B. and B. Jovanovic (2001). The information-technology revolution and the stock market: Evidence. *American Economic Review 91*(5), 1203–1220.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Jones, C. I. (2011). Misallocation, economic growth, and input-output economics. Working paper, Stanford University.

Jorgenson, D. W. and K. J. Stiroh (2000). U.s. economic growth at the industry level. *American Economic Review 90*(2), 161–167.

Klette, T. J. and S. Kortum (2004). Innovating firms and aggregate innovation. *Journal of Political Economy 112*(5), 986–1018.

Kortum, S. (1993). Equilibrium r&d and the patent-r&d ratio: U.s. evidence. *American Economic Review 83*(2), 450–57.

Kortum, S. and J. Lerner (1998, June). Stronger protection or technological revolution: what is behind the recent surge in patenting? *Carnegie-Rochester Conference Series on Public Policy 48*(1), 247–304.

Kortum, S. and J. Lerner (2000, Winter). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics 31*(4), 674–692.

Laitner, J. and D. Stolyarov (2003). Technological change and the stock market. *The American Economic Review 93*(4), pp. 1240–1267.

Lampe, R. and P. Moser (2011). Do patent pools encourage innovation? evidence from 20 industries in the 1930s.

Lentz, R. and D. T. Mortensen (2008, November). An empirical model of growth through product innovation. *Econometrica 76*(6), 1317–1373.

Moser, P. and T. Nicholas (2004). Was electricity a general purpose technology? evidence from historical patent citations. *The American Economic Review, Papers and Proceedings 94*(2), 388–394.

Moser, P., J. Ohmstedt, and P. Rhode (2011). Patents, citations, and inventive output - evidence from hybrid corn.

Moser, P. and A. Voena (2011). Compulsory licensing: Evidence from the trading with the enemy act. *The American Economic Review forthcoming*.

Moser, P., A. Voena, and F. Waldinger (2012). German-jewish emigres and u.s. invention.

Newman, M. (2005). Power laws, Pareto distributions and Zipf's law. *Contemporary Physics 46*(5), 323–351.

Nicholas, T. (2008). Does innovation cause stock market runups? evidence from the great crash. *American Economic Review 98*(4), 1370–96.

Pakes, A. (1985, April). On patents, R&D, and the stock market rate of return. *Journal of Political Economy 93*(2), 390–409.

Ramey, V. A. and M. D. Shapiro (2001, October). Displaced capital: A study of aerospace plant closings. *Journal of Political Economy 109*(5), 958–992.

Restuccia, D. and R. Rogerson (2008, October). Policy distortions and aggregate productivity with heterogeneous plants. *Review of Economic Dynamics 11*(4), 707–720.

Scherer, F. M. (1965). Firm size, market structure, opportunity, and the output of patented inventions. *The American Economic Review 55*(5), pp. 1097–1125.

Scherer, F. M. (1983, March). The propensity to patent. *International Journal of Industrial Organization 1*(1), 107–128.

Shea, J. (1999). What do technology shocks do? In *NBER Macroeconomics Annual 1998, volume 13*. National Bureau of Economic Research, Inc.

Smiley, G. (1994). *The American economy in the twentieth century*. College Division, South-Western Pub. Co.

Appendix A: Data

Business-cycle data

Productivity is utilization-adjusted TFP from Basu et al. (2006). Populations is from the U.S. Census Bureau (http://www.census.gov/popest/national/national.html). Output and consumption are from the Bureau of Economic Analysis. Output is gross domestic product (NIPA Table Table 1.1.5) divided by the consumption price index (St Louis Fed, CPIAUCNS). Consumption is consumption of non-durables plus services, deflated by the price index of non-nudrables and services respectively (NIPA Tables 1.1.5, 2.3.4). To get hours worked, we merge series CEU0500000007 and EEU00500005 from the BLS, times total private employment(BLS, CEU0500000001) divided by population.

Firm-level data

We define the investment rate as capital expenditures (Compustat: capx) divided by lagged gross property, plant and equipment (ppegt); labor hiring as the percentage change in the number of employees (emp); financial capital inflows as debt issuance plus equity issuance minus payout (Compustat sstk + dltis - prstkc-dv-dltr) normalized by assets (at); return on assets as operating income (ib) plus depreciation divided by lagged lagged gross property, plant and equipment; Tobin's Q as the sum of the market value of common equity (CRSP December market capitalization), the book value of debt (dltt), the book value of preferred stock (pstkrv), minus the book value of inventories (invt) and deferred taxes (txdb), divided by gross property, plant and equipment (ppegt); productivity of capital as sales (sale) plus change in inventories (invt) over gross property, plant and equipment (ppegt); productivity of labor as sales (sale) plus change in inventories (invt) over number of employees (emp).

Other Data

The industry-level data is from the KLEMS dataset of Dale Jorgenson. We use industry value added (constant prices) as measure of industry output. The aggregate Tobin's Q is computed using NIPA and FRB Flow of Funds Data as in Laitner and Stolyarov (2003). Finally, the time series information on R&D expenditure spending in the US is obtained from the NSF website.

Tables

Table 1: Number of patents

Data step	Number of patents
Total downloaded patents	7,797,506
Granted in 1926 or later	5,988,864
Identified as having an assignee	4,386,506
Matched to CRSP	1,840,636
Of which:	
Present in NBER data	1,404,822
New to this paper	435,814

The table provides details on patents in our sample. We begin with all patents downloaded from Google Patents, and restrict the sample to post-1926. Not all patents have assignees, and among those that do, not all are companies in CRSP. We are able to match 1,840,636 patents to CRSP firms, of which 435,814 (24%) are new to this study. Further details are reported in Table 2 and Figure 1.

Table 2: Assignee matching by Decade

	Number of patents			Number of unique		Backward citations	
Decade	Total	With assignee	Matched to CRSP	Matched firms	CRSP firms	>1	Average
1926–1929	173,809	63,958	8,858	180	786	72,575	1.1
1930s	442,199	215,613	47,036	351	951	235,268	1.6
1940s	306,827	167,037	60,571	446	1,042	204,908	2.3
1950s	425,066	217,341	82,245	585	1,246	298,767	2.9
1960s	561,300	327,754	163,851	1,166	3,177	430,916	4.1
1970s	636,097	419,033	236,190	2,081	7,204	576,699	8.3
1980s	708,744	579,098	235,532	2,729	11,715	670,862	12.0
1990s	1,109,399	933,428	352,005	3,577	14,882	1,037,054	13.3
2000s	1,625,423	1,463,244	654,345	1,078	11,900	937,052	4.1
All years	5,988,864	4,386,506	1,840,633	8,729	26,660	4,464,101	6.7

The shows summary statistics for patents in our sample by decade. Column 2 shows the total number of patents, and column 3 shows how many patents are identified as having an assignee. Column 4 shows how many of those patents with assignees are matched to a company in CRSP. (The remaining assignees are either individuals, private companies, or the matching process was unable to identify the correct company.) Columns 5 and 6 show how many unique firms there are matched to patents or in CRSP. The final two columns report the number of patents with more than one backward citation, and the average number of backward citations.

Table 3: Stock turnover around patent announcement days

Event	$l = -1$	$l = 0$	$l = 1$	$l = 2$	$l = 3$	$l = 4$
A. Patent grant	-0.396	0.046	0.082	0.074	0.006	-0.377
	(-8.93)	(2.55)	(5.23)	(4.51)	(0.23)	(-9.12)
B. Patent publication	0.094	0.182	0.283	-0.136	0.015	0.147
	(1.65)	(3.72)	(4.33)	(-2.04)	(0.27)	(2.92)

Table shows the output of the regression of stock return turnover ($x_{t+l} = vol_t/shrout_t$) on a dummy variable taking the value 1 if a patent was granted to the firm on day t (Panel A), or the USPTO publicized the grant application of the firm on day t (Panel B). We include firm-year and day-of-week fixed effects. We cluster standard errors by year and report t-statistics in parenthesis. We restrict the sample to firms that have been granted at least one patent.

Table 4: Descriptive statistics on firm-level innovation variables

statistic	A^+_{ft-1}	$\hat{A}_{ft-1}$
Mean	0.055	0.044
St. Dev.	0.169	0.129
Percentiles		
50	0.000	0.000
75	0.014	0.024
90	0.172	0.129
95	0.339	0.250

Table presents descriptive statistics for our firm-level innovation measures A^+ and $\hat{A}$.

Table 5: Number of future citations and announcement day return

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	grant		publication			grant		publication	
	$l=2$	$l=4$	$l=2$	$l=4$		$l=2$	$l=4$	$l=2$	$l=4$
	A: Dollar returns truncated at zero					B: Dollar returns adj for measurement error			
A_i^+	1.117	0.865	0.377	0.267	$\hat{A}_i$	14.002	9.902	2.771	1.933
	(6.53)	(6.28)	(2.35)	(2.42)		(6.74)	(6.77)	(1.68)	(1.66)
Obs.	1842345	1842345	416282	416282	Obs.	1828616	1828616	415254	415254
R^2	0.096	0.096	0.079	0.079	R^2	0.100	0.099	0.079	0.079
	C: Log dollar returns					D: Log dollar returns adj for measurement error			
$\log A_i$	0.704	0.695	0.252	0.256	$\log \hat{A}_i$	0.939	0.941	0.297	0.297
	(7.11)	(6.99)	(3.01)	(2.93)		(7.80)	(7.82)	(2.76)	(2.74)
Obs.	894697	894697	202194	202194	Obs.	1828616	1828616	415254	415254
R^2	0.099	0.101	0.083	0.082	R^2	0.102	0.102	0.084	0.084

Table shows output of a regressions of number of future citations N_i on the dollar return A_i following the day the patent is issued to the firm (columns 1-3) or the details of the patent are disclosed by the USPTO (columns 1-3). We construct the dollar return A_i as the return of the firm minus the return of the market portfolio r_{fd}, times the firm's market capitalization on the day before the announcement in 1982 USb dollars S_{fd-1}. We report results for announcement day d returns only (columns 1 and 4); returns from day d to $d+2$ (columns 2 and 5); and returns from day $d-1$ to $d+4$ (columns 3 and 6). Panel A shows results for dollar returns; Panel B shows results for dollar results truncated at zero; and Panel C shows results for log dollar returns. We control for announcement-year fixed effects and log firm idiosyncratic volatility ($\log \sigma_{ft}$). We cluster standard errors by announcement year and report t-statistics in parenthesis.

Table 6: Which firms innovate?

	A^+				$\hat{A}$			
A_f	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln K_{t-1}$	0.099	0.106	0.116	0.066	0.062	0.067	0.076	0.035
	(42.86)	(43.71)	(46.79)	(39.40)	(39.55)	(40.40)	(43.12)	(34.17)
$\ln Q_{t-1}$		0.052	0.042	0.029		0.035	0.028	0.020
		(19.80)	(15.04)	(17.79)		(19.82)	(14.96)	(20.11)
$\ln RD_{t-1}$			0.103	0.057			0.068	0.030
			(28.53)	(25.24)			(28.38)	(23.07)
$A_{f,t-1}$				0.665				0.742
				(68.24)				(88.33)
Observations	141695	141695	65234	65058	141695	141695	65234	65058
pseudo R^2	0.476	0.490	0.469	0.653	0.644	0.671	0.739	1.242

Table shows Tobit regressions of firm-level innovation A_{ft} on firm characteristics and lagged competitor innovation A_{It-1}. Firm characteristics are log firm size (K_{ft}, gross PPE), log Tobin's Q and log R&D expenditures to book assets $\ln RD$. All specifications include year (T) and industry (I) fixed effects. Standard errors are clustered by firm.

Table 7: Firm-level productivity and Tobin's Q

mpk_{t+1}, mpl_{t+1}	A. Productivity				q_{t+1}	B. Tobin's Q	
	Capital		Labor				
	(1)	(2)	(3)	(4)		(5)	(6)
A^+_{It-1}	-0.066	-0.049	-0.057	-0.046	A^+_{It}	0.031	0.030
	(-6.68)	(-5.03)	(-6.35)	(-5.12)		(2.69)	(2.62)
A^+_{ft-1}	0.060	0.091	0.108	0.128	A^+_{ft}	0.095	0.098
	(5.77)	(8.64)	(11.71)	(13.73)		(7.13)	(7.33)
R^2	0.844	0.847	0.847	0.850	R^2	0.684	0.686
$\hat{A}_{It}$	-0.087	-0.049	-0.084	-0.056	$\hat{A}_{It}$	0.039	0.048
	(-6.27)	(-3.56)	(-6.72)	(-6.47)		(2.62)	(3.16)
$\hat{A}_{ft}$	0.053	0.102	0.132	0.163	$\hat{A}_{ft}$	0.128	0.114
	(3.70)	(7.02)	(10.41)	(12.58)		(7.08)	(6.32)
R^2	0.844	0.847	0.847	0.850	R^2	0.684	0.686
Observations	125678	125678	120020	120020	Observations	123540	123540
Fixed Effects	I,T	I,T	I,T	I,T	Fixed Effects	I,T	I,T
Controls					Controls		
(Size, mpk or mpl)	Y	Y	Y	Y	(Size)	Y	Y
(R_f, R_I, q, σ)	-	Y	-	Y	(R, R_I, y/k, σ)	-	Y

Table shows output of the regression: $x_{ft+1} = a_0 + a_1 A_{ft} + a_2 A_{It} + b Z_{ft} + \gamma_t + c_I + \rho x_{ft} + u_{it}$, where $X_{ft} = [y^K_{ft}, y^L_{ft}, q_{ft}]$ is log productivity of capital, labor and Tobin's Q. Depending on the specification, the vector Z of controls includes lagged values of log Tobin's Q, firm stock return (R), firm volatility (σ, in the case of our truncated measure A^+ only), industry c_I or time γ_t fixed effects. We control for lagged firm size (log capital (Columns 1-2,5-6) or number of employees (Columns 3-4)) and productivity throughout. Standard errors are clustered by firm. All variables are winsorized by year at the 1% level.

Table 8: Firm-level reallocation: Investment

i_{t+1}	(1)	(2)	(3)	(4)	(5)
A^+_{It-1}	-0.046	-0.046	-0.040	-0.031	-0.027
	(-10.35)	(-10.45)	(-12.10)	(-9.78)	(-8.49)
A^+_{ft-1}	0.039	0.047	0.042	0.040	0.031
	(9.13)	(11.02)	(13.29)	(12.79)	(10.14)
R^2	0.085	0.093	0.221	0.260	0.273
$\hat{A}_{It}$	-0.070		-0.059	-0.042	-0.036
	(-12.27)		(-13.52)	(-9.92)	(-8.50)
$\hat{A}_{ft}$	0.040		0.034	0.041	0.039
	(7.10)		(8.23)	(9.96)	(9.66)
R^2	0.085		0.215	0.257	0.273
Observations	126727	126727	126727	126727	126727
Fixed Effects	I,T	I,T	I,T	I,T	I,T
(Size - K)	Y	Y	Y	Y	Y
(σ)	-	Y	Y	Y	Y
(i_{t-1})	-	-	Y	Y	Y
(R_f, R_I, Q)	-	-	-	Y	Y
($MPK, E/K$)	-	-	-	-	Y

Table shows output of the regression:

$$i_t = a_0 + a_1\, A_{ft-1} + a_2\, A_{It-1} + \beta\, Z_{ft-1} + \rho\, i_{t-1} + u_{it}.$$

Here i_t refers to capital expenditures (Compustat item capx) minus sale of property, plant and equipment (Compustat item sppe) over lagged capital stock (Compustat ppegt). Depending on the specification, we control for lagged values of log Tobin's Q, firm size (log capital), sales-to-capital (Y/K), profitability (E/A), firm stock return (R), firm volatility (σ, in the case of our truncated measure A^+ only), industry (I) or time (T) fixed effects, and lagged values of the dependent variable . Standard errors are clustered by firm. All variables are winsorized by year at the 1% level.

Table 9: Firm-level reallocation: Labor hiring

Δh_{t+1}	(1)	(2)	(3)	(4)	(5)
A^+_{It-1}	-0.045	-0.046	-0.046	-0.033	-0.024
	(-7.35)	(-7.60)	(-7.93)	(-5.92)	(-4.30)
A^+_{ft-1}	0.008	0.016	0.024	0.020	0.017
	(1.37)	(2.80)	(4.41)	(3.61)	(3.05)
R^2	0.039	0.044	0.053	0.086	0.090
$\hat{A}_{It}$	-0.062		-0.063	-0.040	-0.029
	(-7.65)		(-8.18)	(-5.22)	(-3.74)
$\hat{A}_{ft}$	-0.008		0.014	0.020	0.017
	(-0.97)		(1.83)	(2.71)	(2.25)
R^2	0.039		0.053	0.086	0.090
Observations	119760	119760	119760	119760	119760
Fixed Effects	I,T	I,T	I,T	I,T	I,T
(Size - H)	Y	Y	Y	Y	Y
(σ)	-	Y	Y	Y	Y
(Δn_{t-1})	-	-	Y	Y	Y
(R_f, R_I, Q)	-	-	-	Y	Y
(MPL, ROA)	-	-	-	-	Y

Table shows output of the regression:

$$\Delta n_t = a_0 + a_1\, A_{ft-1} + a_2\, A_{It-1} + \beta\, Z_{ft-1} + \rho\, i_{t-1} + u_{it}.$$

Here Δn_t refers to log employment growth (Compustat item emp). Depending on the specification, we control for lagged values of firm size (log no. of employees), sales-to-employees (Y/N), earnings to assets (ROA), firm stock return (R), firm volatility (σ, in the case of our truncated measure A^+ only), industry (I) or time (T) fixed effects, and lagged values of the dependent variable. Standard errors are clustered by firm. All variables are winsorized by year at the 1% level.

Table 10: Firm-level reallocation: Financial inflows

e_{ft+1}	(1)	(2)	(3)	(4)	(5)
A^+_{It-1}	-0.007	-0.006	-0.008	-0.001	-0.009
	(-1.28)	(-1.22)	(-1.84)	(-0.32)	(-2.08)
A^+_{ft-1}	0.043	0.037	0.034	0.025	0.014
	(6.80)	(5.90)	(6.30)	(4.56)	(2.81)
R^2	0.114	0.117	0.155	0.184	0.219
$\hat{A}_{It}$	-0.017		-0.017	-0.005	-0.018
	(-2.32)		(-2.68)	(-0.82)	(-2.86)
$\hat{A}_{ft}$	0.052		0.046	0.048	0.022
	(6.03)		(6.25)	(6.28)	(3.09)
R^2	0.114		0.154	0.182	0.219
Observations	126727	126727	126727	126727	126727
Fixed Effects	I,T	I,T	I,T	I,T	I,T
(Size - K)	Y	Y	Y	Y	Y
(σ)	-	Y	Y	Y	Y
(Δfin_{ft-1})	-	-	Y	Y	Y
(R_f, R_I, Q)	-	-	-	Y	Y
(ROA)	-	-	-	-	Y

Table shows output of the regression:

$$fin_{ft} = a_0 + a_1\, A_{ft-1} + a_2\, A_{It-1} + \beta\, Z_{ft-1} + \rho\, i_{t-1} + u_{it}.$$

Here fin_{ft} refers to the ratio of total financial inflows, defined as debt issuance plus equity issuance minus payout (Compustat sstk + dltis - prstkc-dv-dltr), over book assets. Depending on the specification, we control for lagged values of firm size (log capital), log Tobin's Q, earnings to book assets (ROA), firm stock return (R), firm volatility (σ, in the case of our truncated measure A^+ only), industry (I) or time (T) fixed effects, and lagged values of the dependent variable. Standard errors are clustered by firm. All variables are winsorized by year at the 1% level.

Table 11: Industry reallocation

x_{t+1}	Quantity of capital services, growth				Quantity of labor services			
A^+_{It}	0.018	0.015	0.026	0.022	0.024	0.032	0.031	0.039
	(2.02)	(1.78)	(3.11)	(2.49)	(1.42)	(1.88)	(1.82)	(2.35)
A^+_{MIt}	-0.112	-0.069			-0.274	-0.207		
	(-7.21)	(-3.72)			(-7.56)	(-4.60)		
R^2	0.037	0.098	0.165	0.184	0.051	0.080	0.164	0.186
$\hat{A}_{It}$	0.023	0.015	0.032	0.027	0.021	0.036	0.029	0.043
	(1.99)	(1.39)	(2.83)	(2.24)	(0.94)	(1.73)	(1.34)	(2.09)
$\hat{A}_{MIt}$	-0.153	-0.126			-0.263	-0.239		
	(-8.77)	(-4.31)			(-6.35)	(-5.49)		
R^2	0.048	0.094	0.164	0.184	0.033	0.072	0.163	0.183
x_{t+1}	Price of capital services				Price of labor services			
A^+_{It}	-0.026	-0.019	-0.038	-0.031	0.005	0.008	0.005	0.005
	(-0.96)	(-0.70)	(-1.39)	(-1.10)	(0.78)	(1.19)	(0.74)	(0.75)
A^+_{MIt}	0.022	0.088			0.099	0.123		
	(0.36)	(1.24)			(7.00)	(7.03)		
R^2	0.005	0.030	0.145	0.166	0.082	0.091	0.357	0.361
$\hat{A}_{It}$	-0.048	-0.029	-0.063	-0.043	0.007	0.009	0.007	0.009
	(-1.38)	(-0.85)	(-1.84)	(-1.24)	(0.74)	(0.89)	(0.71)	(0.94)
$\hat{A}_{MIt}$	0.110	0.146			0.114	0.118		
	(1.36)	(1.79)			(6.30)	(6.43)		
R^2	0.007	0.031	0.146	0.166	0.079	0.081	0.357	0.360
Observations	1395	1395	1395	1395	1395	1395	1395	1395
Controls								
(R, σ)	-	Y	-	Y	-	Y	-	Y
Time Effects	-	-	Y	Y	-	-	Y	Y

Table reports results from a regression of the quantity $[k, h]$ and price $[p, w]$ of capital and labor services on the amount of innovation at the industry level $[A_I]$ and on the amount of innovation of all other industries $[A_{MI}]$. We control for time effects (T), industry stock return R^I, industry volatility σ^I (in the case of our truncated measure A^+ only) and one lag of the dependent variable. Data is from Dale Jorgenson's 35-sector KLEM, described in Jorgenson and Stiroh (2000). Sample is 1960-2005 and covers 31 industries after excluding the finance, utilities and government enterprises sector. We report t-statistics in parenthesis, with errors clustered by industry.

Table 12: Innovation and Firm Exit

x_{t+1}	Rate of establishment exit			
A^+_{It}	0.882	0.881	1.057	0.746
	(3.48)	(3.45)	(2.49)	(1.85)
A^+_{MIt}	-2.740	-2.778		
	(-1.52)	(-1.49)		
R^2	0.502	0.502	0.732	0.763
$\hat{A}_{It}$	1.313	1.322	2.227	2.171
	(2.14)	(2.20)	(3.31)	(2.94)
$\hat{A}_{MIt}$	-4.691	-4.745		
	(-1.32)	(-1.38)		
R^2	0.509	0.510	0.732	0.735
Observations	231	231	231	231
Controls				
(R, σ)	-	Y	-	Y
Time Effects	-	-	Y	Y

Table reports results from a regression of the rate of establishment exit on the amount of innovation at the industry level $[A_I]$ and on the amount of innovation of all other industries $[A_{MI}]$. We include industry fixed effects throughout. Depending on the specification, we include time effects (T), industry stock return R^I, and industry volatility σ^I (in the case of our truncated measure A^+ only). Data is from the tables of Business Dynamics Statistics at the US Census, and cover 7 industries, after dropping the finance sector and utilities, over the period 1977 to 2009. Industries correspond to the one-digit SIC code level. We report t-statistics in parenthesis, with standard errors clustered by year.

Table 13: Granger causality tests

Variable	Variable does not Granger cause A		A does not Granger cause variable	
	A	$\hat{A}$	A	$\hat{A}$
Output and productivity				
Productivity	0.246	0.634	0.006	0.001
Output	0.523	0.121	0.068	0.848
Technology measures of Alexopoulos (2011)				
Bowkers technology books	0.236	0.224	0.131	0.704
Library of Congress new technology books	0.111	0.005	0.615	0.647
Computer software and hardware books	0.386	0.477	0.579	0.245
Computer software, hardware, and network books	0.383	0.484	0.626	0.245
Telecommunications books	0.501	0.962	0.237	0.054
Other technology measures				
R&D Spending	0.672	0.988	0.448	0.456

Table features p-values of Granger causality tests, based on a 3-variable VAR $[X_t, \sigma_t, A_t]$ with a deterministic trend.

Table 14: Innovation and Tobin's Q

$\Delta \log Q_t$	A. Benchmark Measure			B. Alt. Normalization		
$\Delta \log A_t^+$	-0.182	-0.256	-0.218	-0.199	-0.194	-0.143
	(-4.88)	(-6.14)	(-3.91)	(-5.09)	(-4.89)	(-2.66)
R^2	0.253	0.373	0.387	0.266	0.297	0.305
$\Delta \log \hat{A}_t$	-0.185	-0.223		-0.196	-0.188	
	(-3.87)	(-4.17)		(-3.83)	(-3.67)	
R^2	0.188	0.266		0.186	0.223	
Observations	58	58	58	58	58	58
$(\log A_{t-1})$	-	Y	Y			
$(\log Q_{t-1})$	-	Y	Y			
$(\Delta \log \sigma_t)$	-	-	Y			

Table shows output of a regression of changes in log Tobin's Q at the firm (Panel A) or aggregate level (B) on our measure of innovation, controlling for changes in volatility (in the case of our truncated measure A^+ only) and lagged value of Q and innovation measures. Sample is 1952-2008. Results in Panel A use data from Compustat, include time-fixed effects and standard errors clustered at the firm level. Results in Panel B use data from the flow of funds, and standard errors are computed using the Newey-West estimator.

Figure 1: Number of Patents with Matched Assignees

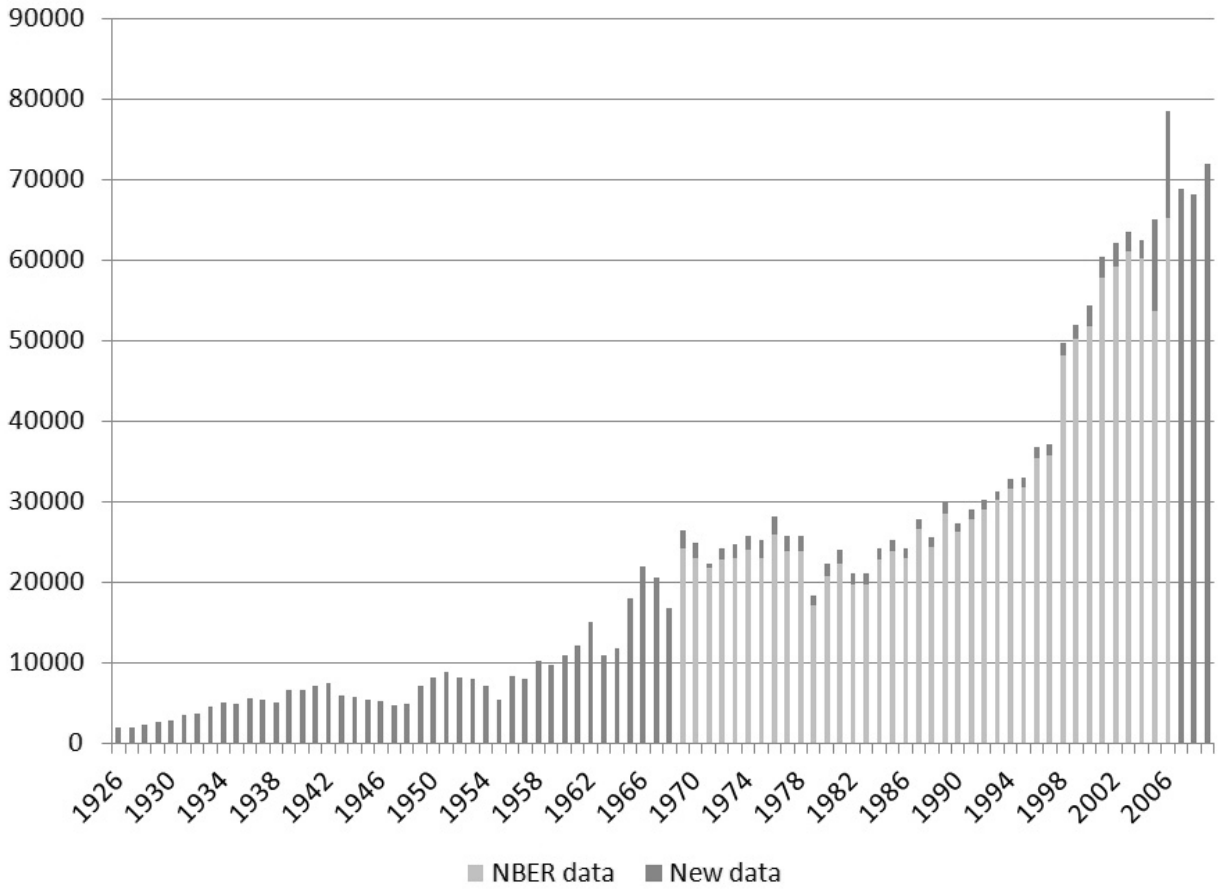
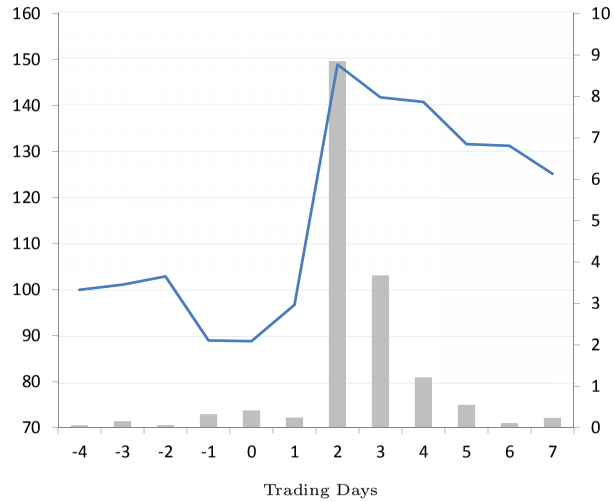
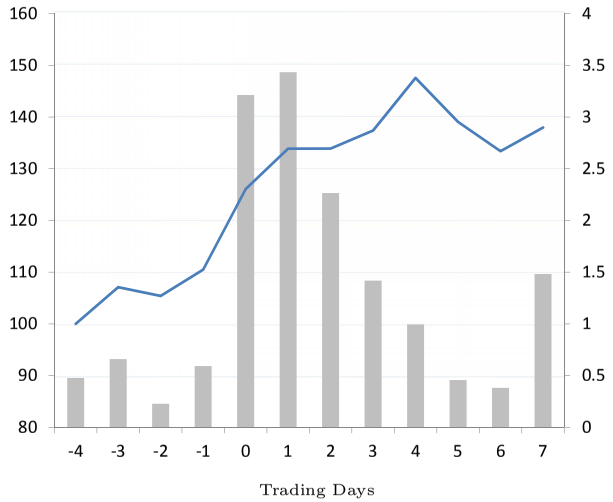


Figure shows the number of patents matched to CRSP firms by year of patent grant. Light shading denotes patents included in the NBER patent data set, while dark shading denotes patents that are new in our paper.

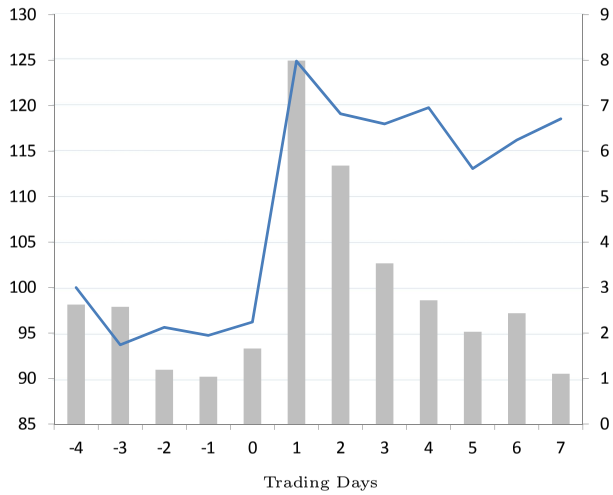
Figure 2: Some illustrative examples



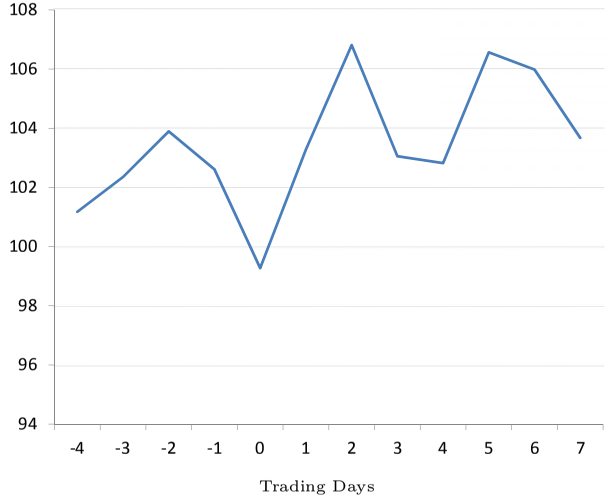
(a) Patent 4,946,778 granted to Genex on Aug, 7 1990, "Single Polypeptide Chain Binding Molecules."



(b) Patent 5,585,089 granted to Protein Design on Dec 17, 1996, "Humanized Immunoglobulins."



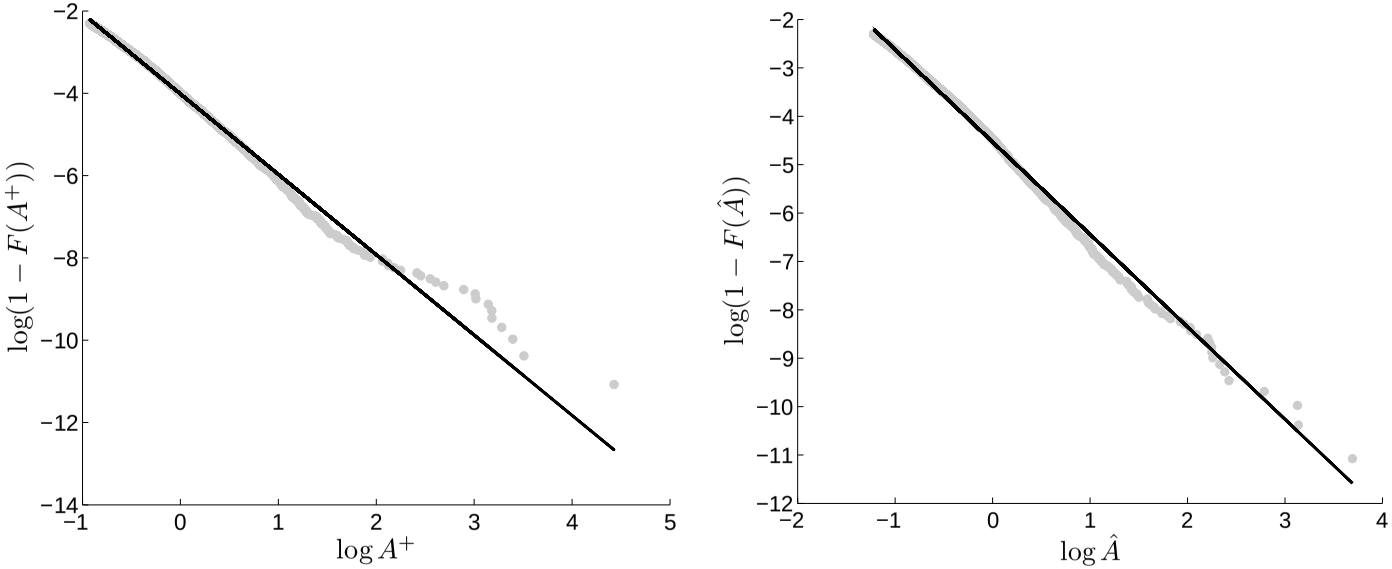
(c) Patent 6,317,722 granted to Amazon.com on Nov 13, 2001, "Use Of Electronic Shopping Carts To Generate Personal Recommendations."



(d) Patent 4,345,262 granted to Canon on Aug 17, 1982, "Ink Jet Recording Method."

Figure plots cumulative abnormal returns (left axis) and turnover (right axis) around the date the patent is granted for illustrative examples discussed in the text. Note that Canon reported a 6% fall in pre-tax profits on Aug 19 (two days subsequent to the patent grant).

Figure 3: Firm innovation measures – Tail distribution

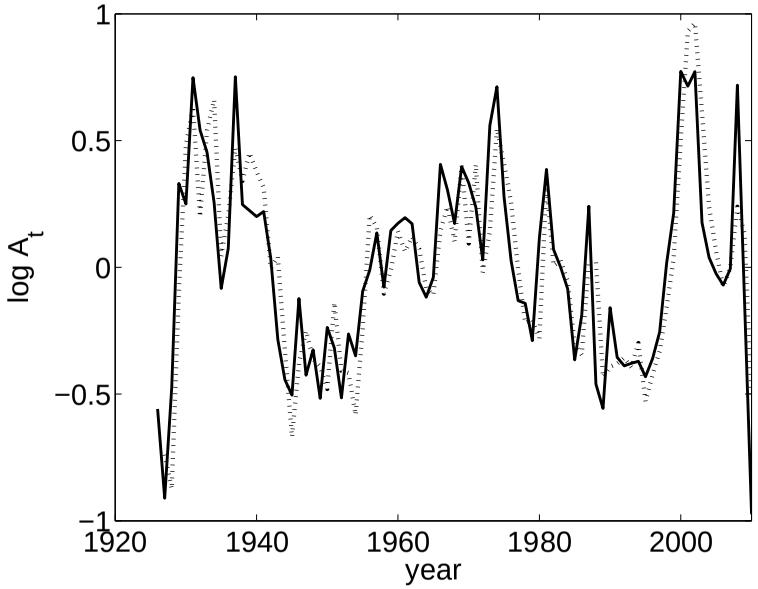


(a) Firm innovation measure A_f^+, truncated

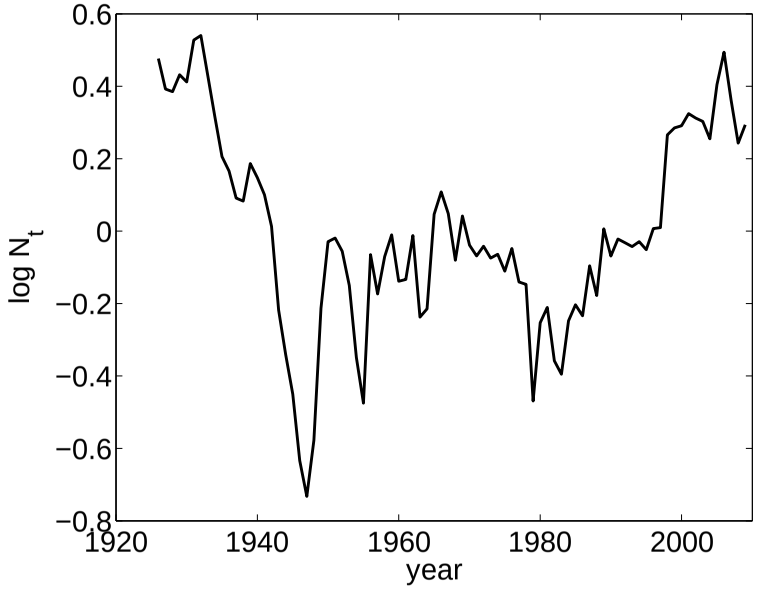
(b) Firm innovation measure $\hat{A}_f$, adjusted for measurement error

Figure plots the log complementary empirical cdf, $\log(1 - F(A))$, versus the log value of the firm-level innovation measure, $\log A$, for the top 10 percent of the distribution.

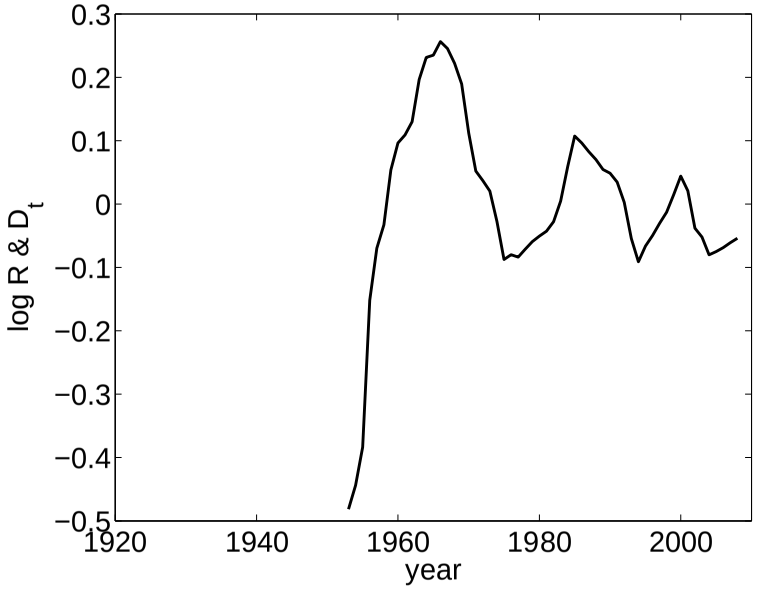
Figure 4: Aggregate measures of innovation



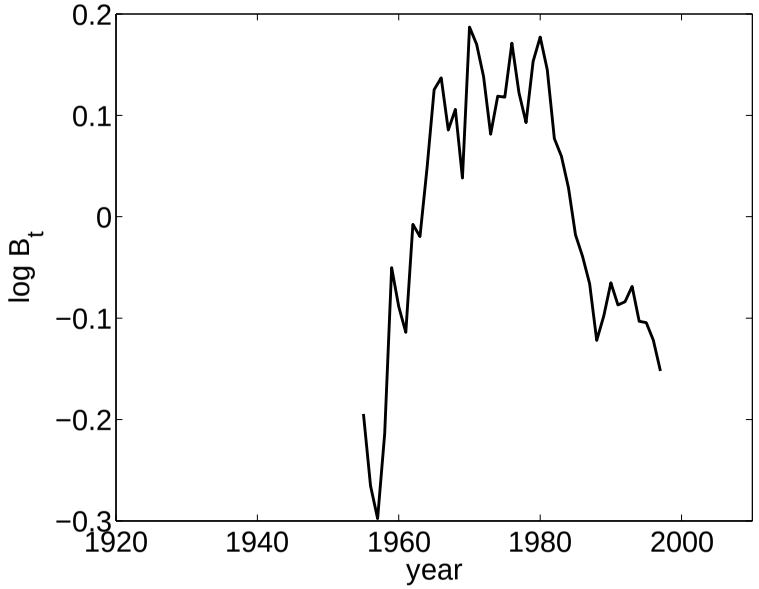
(a) Innovation A_t



(b) Number of patents



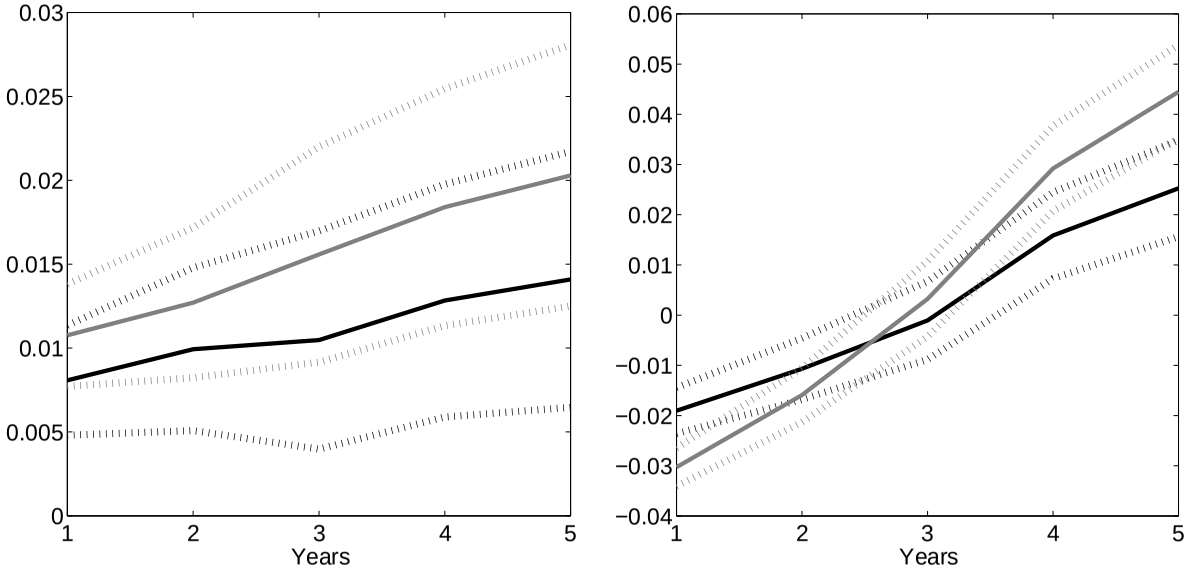
(c) R&D Stock



(d) New technology books (Library of Congress)

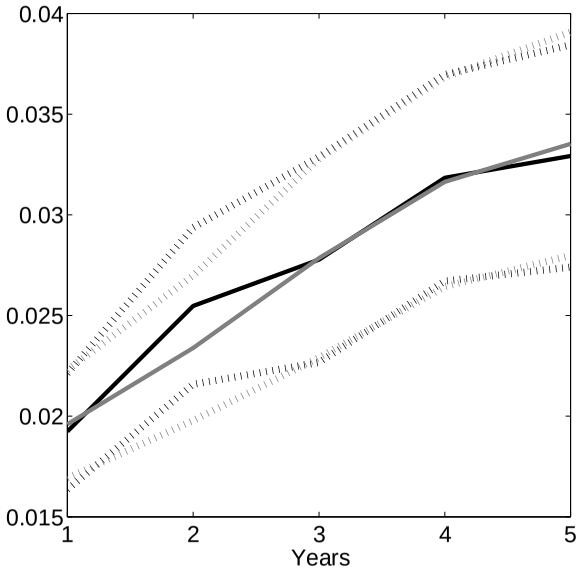
Figure plots log values of a) our measure of innovation A^+ (solid line) and $\hat{A}$ (dotted line) ; b) total number of patents granted; c) R&D Capital stock (from BEA); d) number of new technology books in the Library of Congress (from Alexopoulos (2011)).

Figure 5: Firm productivity – Dynamic response

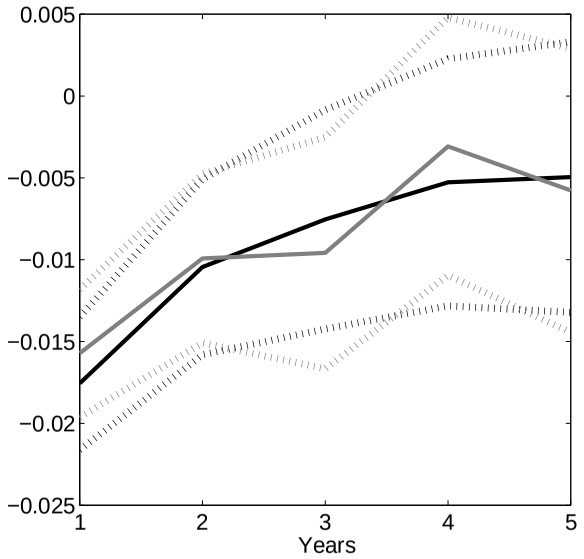


(a) Capital productivity to own innovation A_f

(b) Capital productivity to competitor innovation A_I



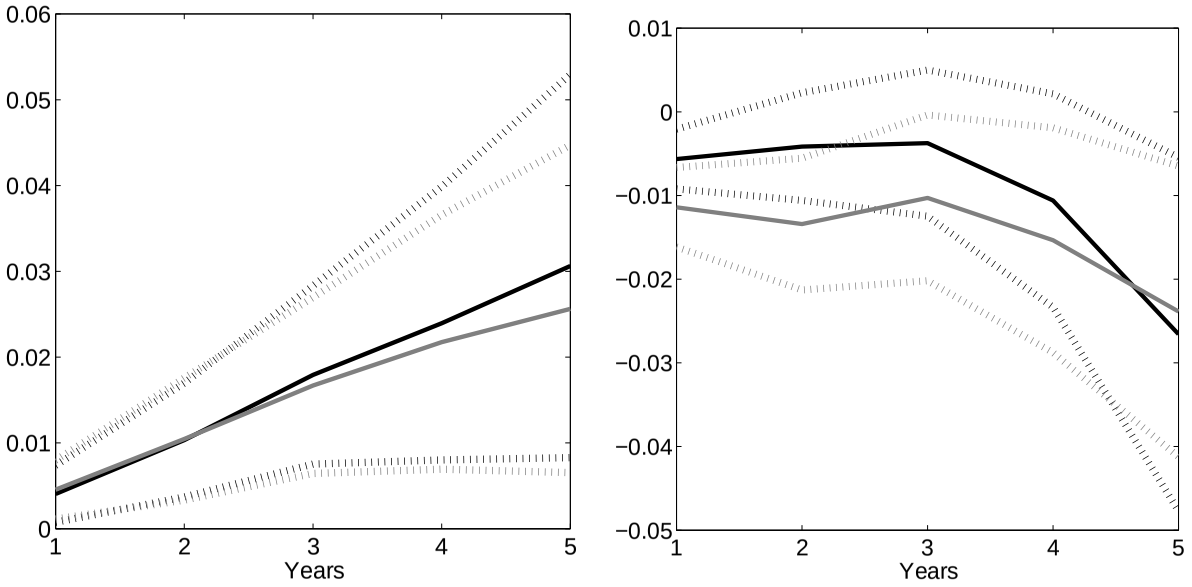
(c) Labor productivity to own innovation A_f



(d) Labor productivity to competitor innovation A_I

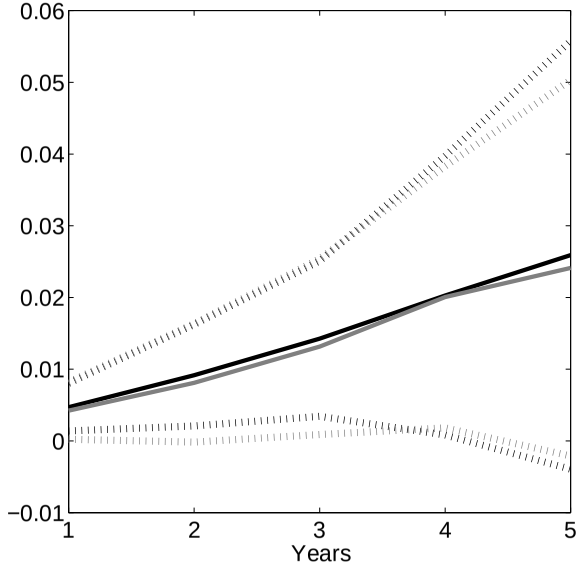
Figure plots coefficients $a_1(k)$ and $a_2(k)$ (and 90% confidence intervals) of a regression of long-run capital (left panel) or labor (right panel) firm-level productivity on innovation of firm (A_f) and competitors (A_I): $y_{ft+k} = a_0 + a_1(k)\, A_{ft-1} + a_2(k)\, A_{It-1} + \beta(k)\, Z_{ft-1} + \rho(k)\, y_{ft-1} + u_{it}$. The vector Z of controls includes lagged values of firm size (log capital or number of employees), log Tobin's Q, firm stock return (R), firm volatility (σ, in the case of our truncated measure A^+ only), industry (I) or time (T) fixed effects. More details on estimation are in the text. Grey lines correspond to results using our measure of innovation A^+ based on simple truncation; black lines correspond to results using our measure of innovation $\hat{A}$ that accounts for measurement error.

Figure 6: Industry productivity – Dynamic response

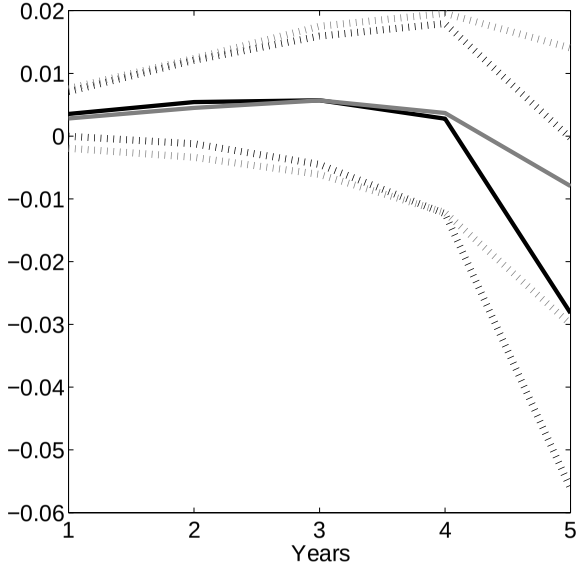


(a) Capital productivity to own innovation A_I

(b) Capital productivity to aggregate A_M



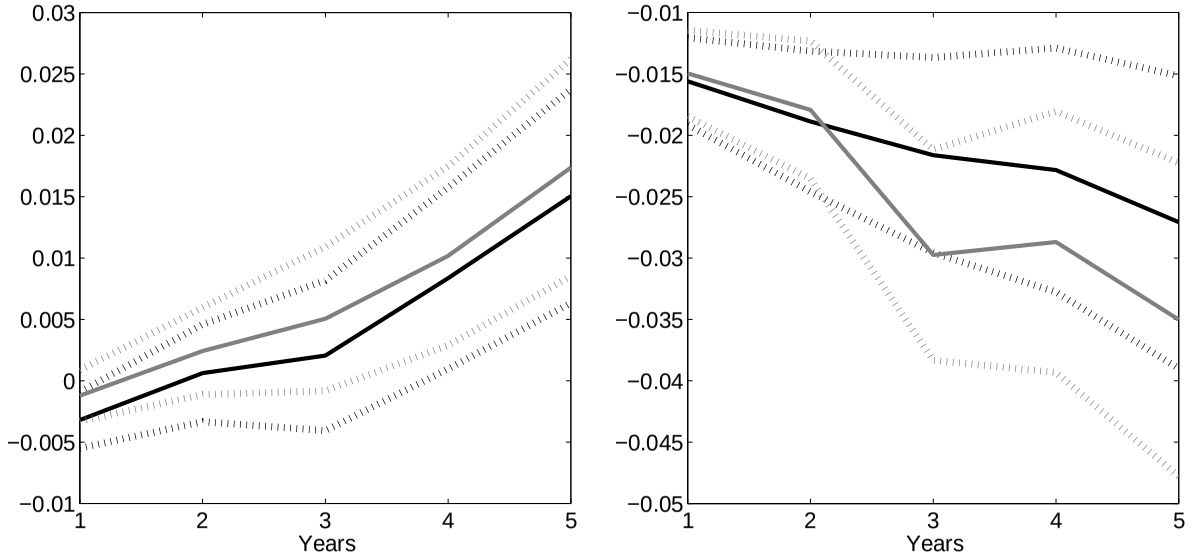
(c) Labor productivity to own innovation A_I



(d) Labor productivity to aggregate A_M

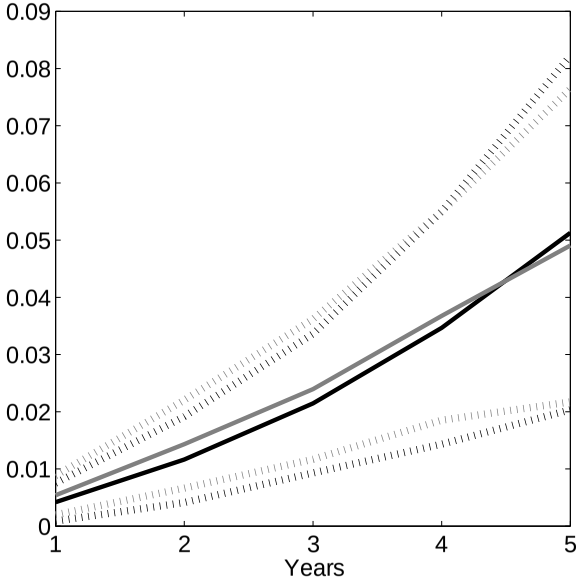
Table plots coefficients from a regression of log output y relative to aggregate output, capital mpk and labor productivity mpl on amount of innovation A_I at the industry level, and the aggregate amount of innovation excluding that industry A_M. Controls include industry stock return; industry volatility (in the case of our truncated measure A^+ only); lagged capital productivity (panels a and b); lagged labor productivity (panels c and d); and lagged output growth (panels e and f); Data is from Dale Jorgenson's 35-sector KLEM. We plot coefficient estimates and 90% confidence intervals using standard errors clustered by industry. Grey lines correspond to results using our measure of innovation A^+ based on simple truncation; black lines correspond to results using our measure of innovation $\hat{A}$ that accounts for measurement error. Right hand-side variables are standardized to unit standard deviation.

Figure 7: Firm and industry output – Dynamic response

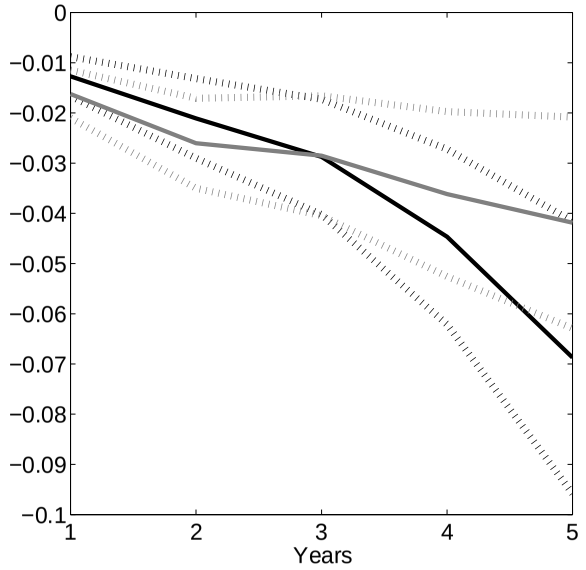


a) Output to own innovation A_f

(b) Output to aggregate A_{If}



(c) Output to own innovation A_I



(d) Output to aggregate A_M

Figure plots coefficients $a_1(k)$ and $a_2(k)$ (and 90% confidence intervals) of a regression of long-run capital (left panel) or labor (right panel) firm-level productivity on innovation of firm (A_f) and competitors (A_I): $y_{ft+k} = a_0 + a_1(k)\, A_{ft-1} + a_2(k)\, A_{It-1} + \beta(k)\, Z_{ft-1} + \rho(k)\, y_{ft-1} + u_{it}$. The vector Z of controls includes lagged values of firm size (log capital or number of employees), log Tobin's Q, firm stock return (R), firm volatility (σ, in the case of our truncated measure A^+ only), industry (I) or time (T) fixed effects. More details on estimation are in the text. Grey lines correspond to results using our measure of innovation A^+ based on simple truncation; black lines correspond to results using our measure of innovation $\hat{A}$ that accounts for measurement error.

Figure 8: Innovation and Industry Growth

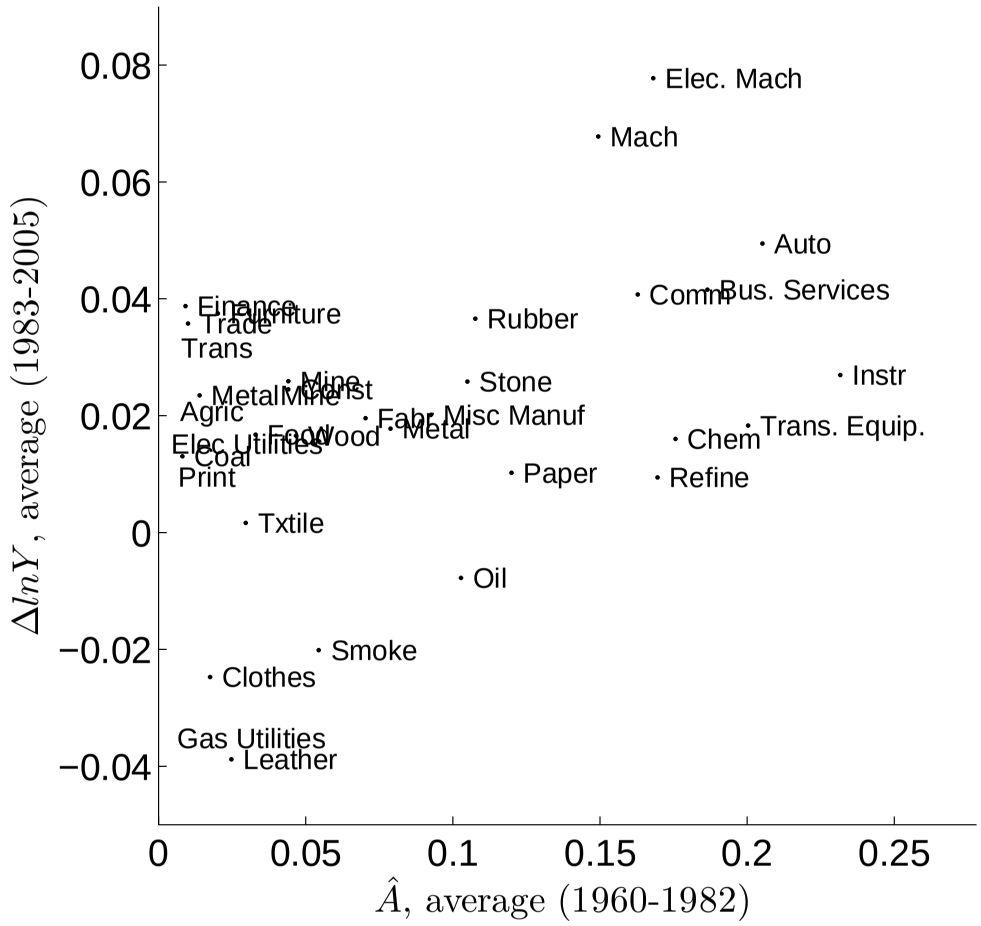
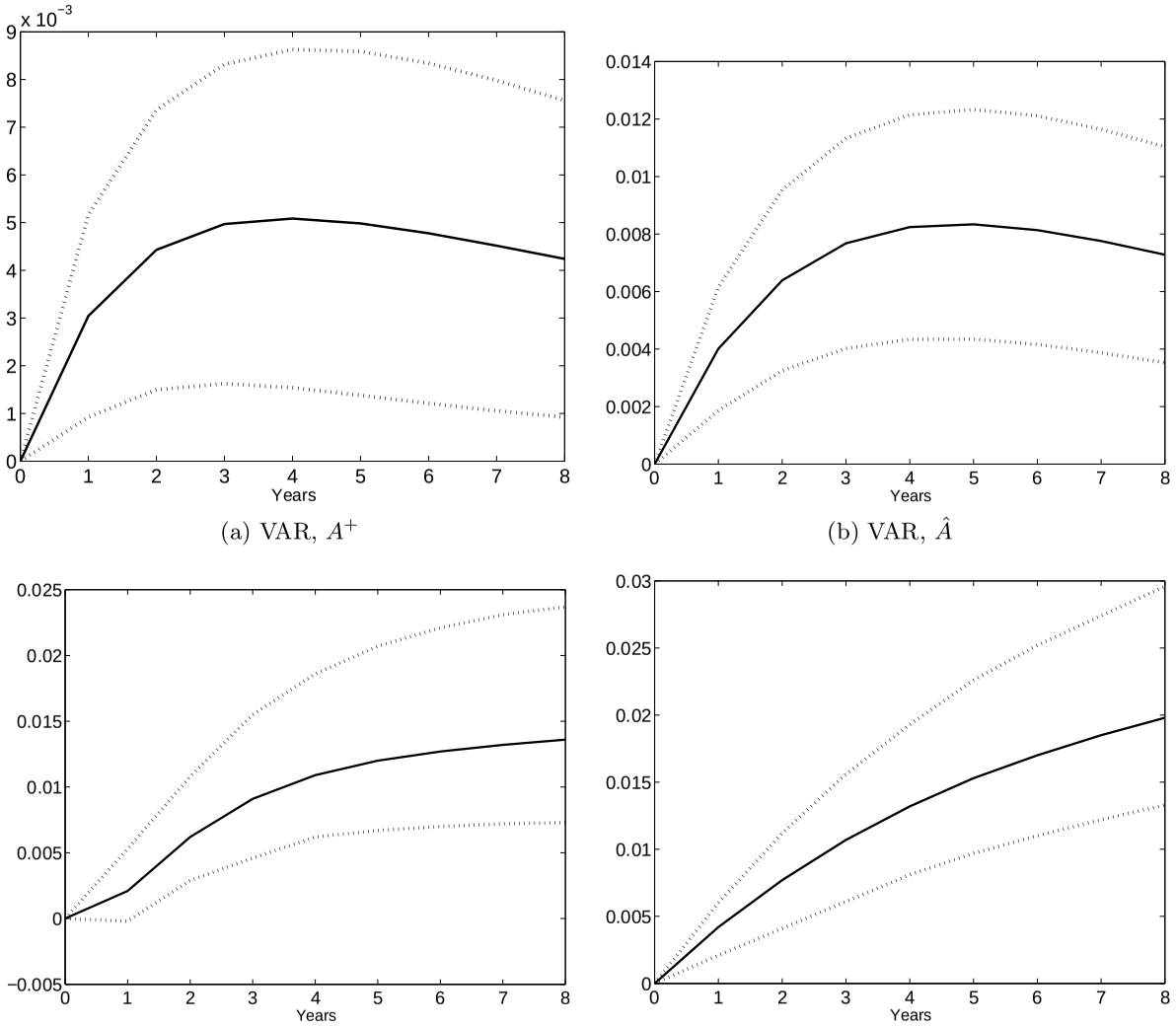


Figure plots the average output growth rate of 34 industries during the 1983-2006 period, versus the amount of innovation in 1960-1982. We use our innovation measure adjusted for measurement error $\hat{A}$. Data is from Dale Jorgenson's website. Output is measured as value added in constant prices.

Figure 9: Impulse responses, Productivity



(a) VAR, A^+

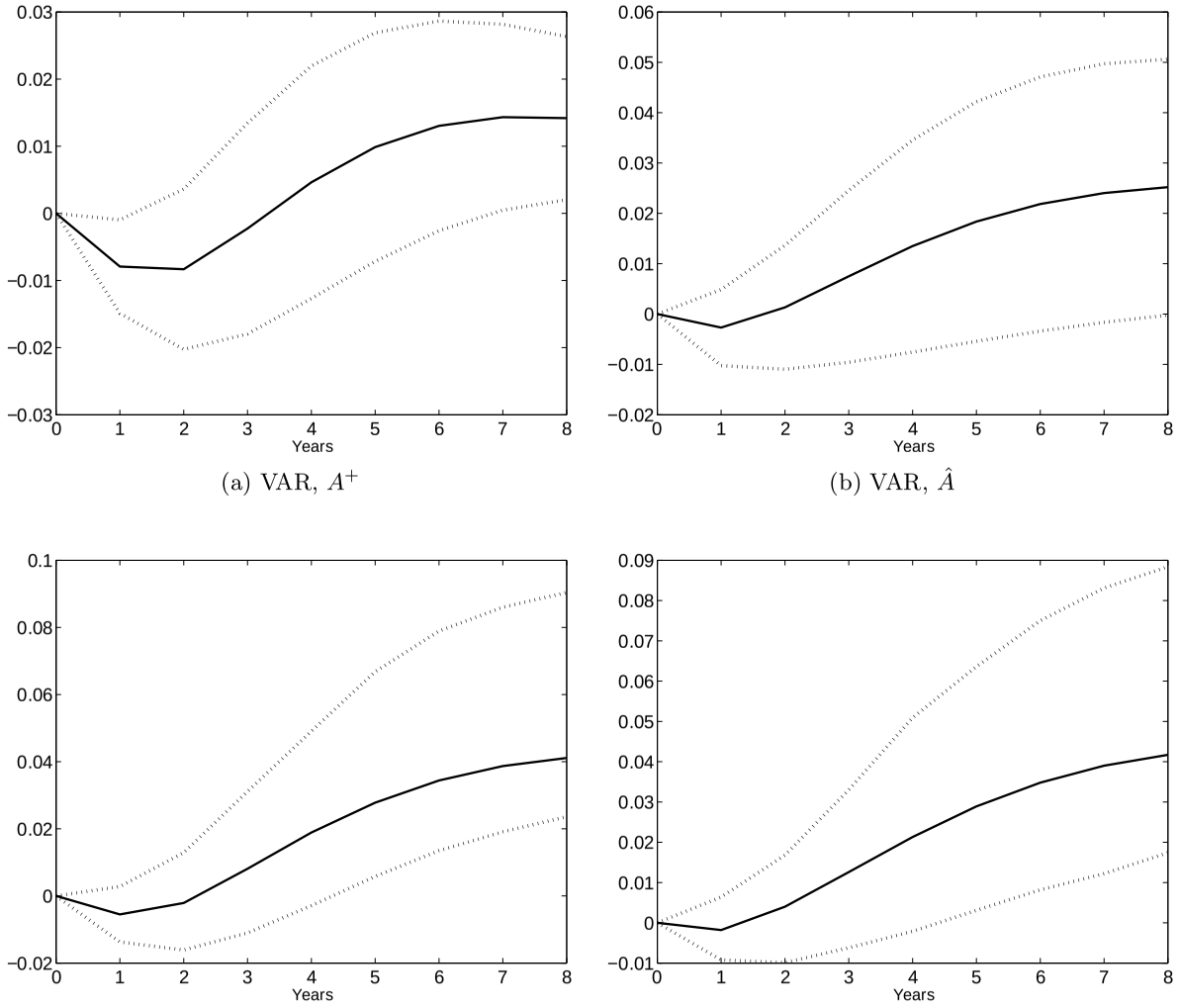
(b) VAR, $\hat{A}$

(c) VECM, A^+

(d) VECM, $\hat{A}$

Figure shows impulse response of productivity from a VAR (top) and VECM (bottom). We obtain impulse responses by ordering our innovation measure last. Panels a and c present results using our measure of innovation A based on simple truncation. Panels b and d present results using our measure of innovation $\hat{A}$ that accounts for measurement error. We include a deterministic trend in all specifications. We select lag length based on the AIC criterion. In panels a and c we include the log cross-sectional average of idiosyncratic volatility. Dotted lines represent 90% confidence intervals using standard errors are computed using 500 bootstrap simulations.

Figure 10: Impulse responses, Output

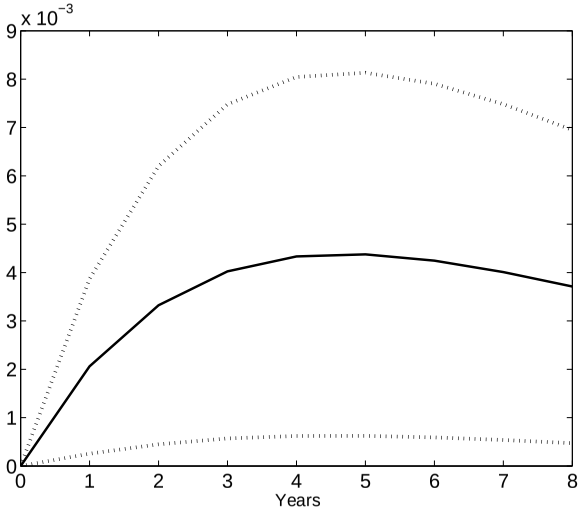


(a) VAR, A^+ (b) VAR, $\hat{A}$

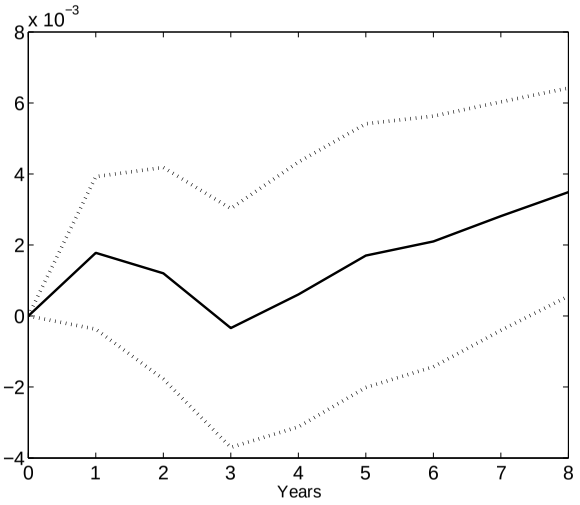
(c) VECM, A^+ (d) VECM, $\hat{A}$

Figure shows impulse response of output from a VAR (top) and VECM (bottom). We obtain impulse responses by ordering our innovation measure last. Panels a and c present results using our measure of innovation A based on simple truncation. Panels b and d present results using our measure of innovation $\hat{A}$ that accounts for measurement error. We include a deterministic trend in all specifications. We select lag length based on the AIC criterion. In panels a and c we include the log cross-sectional average of idiosyncratic volatility. Dotted lines represent 90% confidence intervals using standard errors are computed using 500 bootstrap simulations.

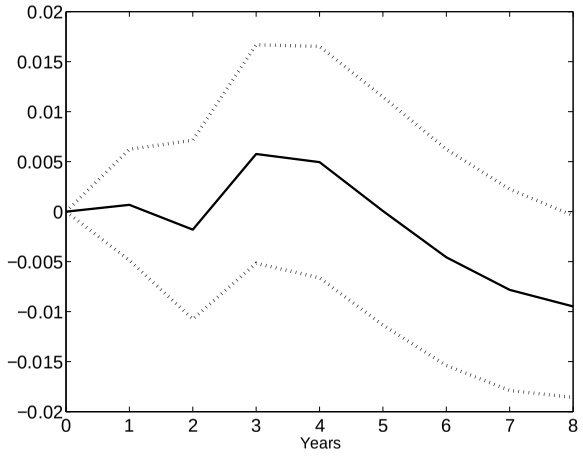
Figure 11: Impulse responses using Number of Patents and R&D Stock



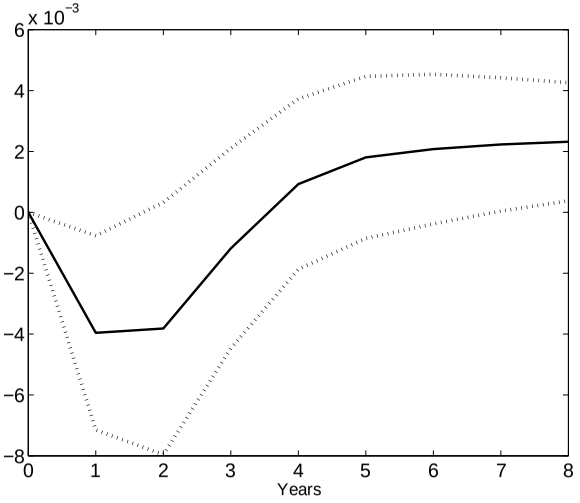
(a) No. patents - Productivity



(b) R&D Stock - Productivity



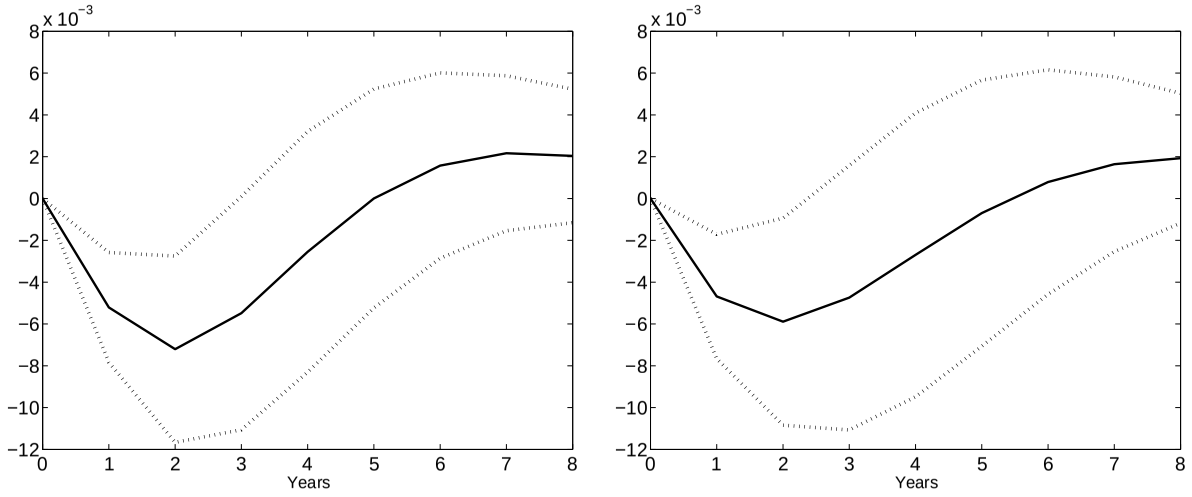
(c) No. patents - Output



(d) R&D Stock - Output

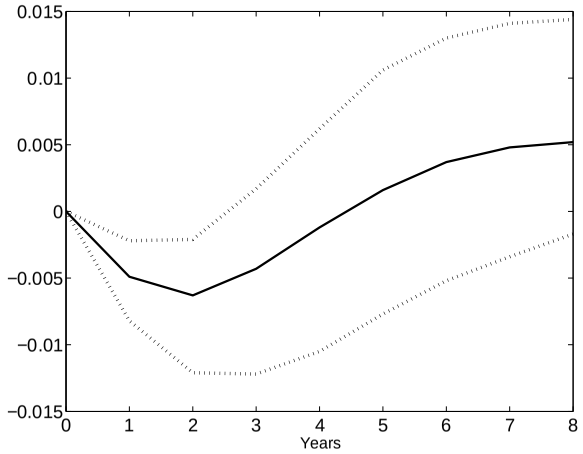
Left panel shows impulse response of log productivity, output and consumption from a bi-variate VAR $[\log X_t, \log N_t]$ with a deterministic trend. Right panel shows impulse response of log productivity, output and consumption from a bi-variate VAR $[\log X_t, \log RD_t]$ with a deterministic trend. Dotted lines represent 90% confidence intervals.

Figure 12: Impulse responses, Consumption

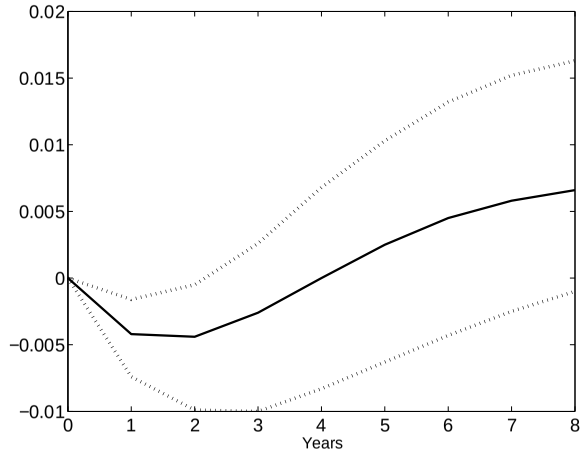


(a) VAR, A^+

(b) VAR, $\hat{A}$



(c) VECM, A^+



(d) VECM, $\hat{A}$

Figure shows impulse response of output from a VAR (top) and VECM (bottom). We obtain impulse responses by ordering our innovation measure last. Panels a and c present results using our measure of innovation A based on simple truncation. Panels b and d present results using our measure of innovation $\hat{A}$ that accounts for measurement error. We include a deterministic trend in all specifications. We select lag length based on the AIC criterion. In panels a and c we include the log cross-sectional average of idiosyncratic volatility. Dotted lines represent 90% confidence intervals using standard errors are computed using 500 bootstrap simulations.