Technological Innovation, Resource Allocation and Growth*

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New version – Preliminary and Incomplete

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. We use our innovation measure to directly test the predictions of a Schumpeterian growth model, where innovation takes the form of quality improvements in existing product lines. Our innovation measure is associated with significant patterns of capital and labor reallocation, increases in productivity and output growth.

JEL classifications: G14, E32, O3, O4

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Economists since Schumpeter have argued that technological innovation is the driver of long-term economic growth. Models of endogenous growth have rich testable predictions about both aggregate quantities and the cross-section of firms, linking improvements in the technology frontier to resource reallocation and subsequent economic growth. However, the predictions of these models are difficult to test directly and quantify mainly due to the scarcity of directly observable measures of technological innovation. This paper aims to fill this gap.

We construct a novel economic measure of innovation that combines information from a patent dataset with stock market data over the period 1926 to 2010.[1] Patents provide useful direct information about technological innovation going as far back as the eighteenth century. However, since patents are highly heterogeneous in their economic value, an increase in the number of patents granted need not coincide with greater technological innovation. Thus, constructing an empirical measure of technological innovation using patent data poses a significant challenge. Our central idea is to use the stock market reaction around the day each patent is granted to appropriately weigh its information content.

We interpret the stock price reaction to successful patent grants using a model along the lines of Grossman and Helpman (1991). In our model, technological innovation manifests as quality improvements in existing product lines.[2] Our model retains the key feature of the framework – growth through creative destruction – but we allow both the aggregate rate of technological progress, as well as the quality improvement each innovation represents, to be stochastic. Patents are valuable to their owners because they restrict competition among producers of the leading product vintages. Following a successful patent application, the prior uncertainty about the applying firm's ability to extract monopoly rents going forward is resolved, resulting in the firm's stock price appreciation. The magnitude of this stock price appreciation is increasing in the market value of the patent, which is a function of the quality of the latest vintage as well as the quality improvement embodied in the good covered by the patent. Summing these stock market responses at the firm level reveals the firm's success at

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

[2] Not all innovation is patentable. However, innovation that is embodied in new products is more easily patentable (see for example Comin, 2008, for a discussion on patentable innovation). Hence, when we are measuring innovation through patents we are capturing technological change embodied in new products.

innovation and the resulting advantage over its competitors. Aggregating across firms with successful patent applications reveals the rate of aggregate technological progress.

Prior to examining the model's predictions, we first obtain evidence confirming our view that stock market reactions to patent issues are informative about patent quality. First, we find that trading activity in the stock of the firm issued a patent increases after the patent issuance date. Second, we find that the firm's stock market reaction to the patent grant is a strong predictor of the number of citations the patent receives in the future, a valuable independent measure of the realized value of a patent. This correlation is robust to a number of patent- and firm-level controls. Placebo experiments suggest that it is unlikely to be driven by unobserved firm heterogeneity.

Armed with a direct measure of a firm's technological progress, we examine the model's empirical predictions about growth and reallocation. First, we find that increased innovation by the firm – relative to its competitors – is linked to subsequent increases in its measured total factor productivity (TFP). Second, consistent with economic optimization, we document a flow of resources – capital and labor – to firms that successfully innovate away from their competitors that do not. Third, consistent with Schumpeter's notion of "creative destruction", we find that an increase in the rate of innovation of competitors relative to the firm is associated with an increased likelihood of firm exit. Overall, we find that successful innovation is an important determinant of firm growth.

An increase in the aggregate rate of innovation is associated with reallocation of inputs and dispersion in firm productivity and growth, since some firms lose market share while others benefit. However, the net economic gain from this reallocation can be small, especially if each innovation represents only a marginal improvement over the previous product vintage. To study this question, we examine the net effects of innovation in two ways. First, we use the point estimates from our firm-level regressions to construct aggregate effects, by netting out the positive and negative effects of innovation on new capital and job creation and firm revenue. We find the net effect of innovation on new capital formation and new job creation to be economically small; innovation leads mostly to reallocation of existing resources among firms. By contrast, we find that in terms of firm growth, innovation has a positive net effect.

However, this analysis is based on a sample of continuing firms. Hence, as a second step, we examine the aggregate effects of innovation using aggregate data.

We construct measures of innovation at the industry and aggregate level by combining the firm-level measures. These aggregate measures are correlated with measures of job reallocation and firm exit at the industry level, but not job creation. Further, the industry-level measures are positively correlated with industry growth. Last, our economy-level measures exhibits substantial correlation with aggregate total factor productivity and output growth. These findings complement the findings from our firm-level analysis and confirm the view that innovation drives growth through creative destruction.

Our measure of technological innovation captures known periods of high technological progress as well as firms participating in these waves (e.g., technologically progressive 1960s and early 1970s, see Laitner and Stolyarov, 2003). The average estimated value per patent exhibits broadly similar low-frequency behavior as the R&D to patents ratio, providing direct support and complementing the findings of Kortum (1993) who argues that the secular increase in R&D spending per patent reflects increased patent valuations rather than a decline in the productivity of the research sector. In addition, the empirical distribution of our 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 describing 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).

We should emphasize that even though our empirical analysis is motivated by a specific model, the insights we obtain are more general and are common in a variety of models of endogenous growth (see Acemoglu, 2009, for a textbook treatment). Our model considers in detail the link between the economic value of the innovation and firm's stock market reaction to a successful patent issues. However, despite the additional details that serve to interpret our measure, the model's predictions are similar to the existing models we build on (e.g. Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1997; Klette and

Kortum, 2004). Hence, our empirical findings should be interpreted as providing support for the general hypothesis that technological innovation is a significant driver of both economic growth and creative destruction. We are not the first to study the link between innovation and firm growth dynamics (Caballero and Jaffe, 1993; Lentz and Mortensen, 2008; Akcigit and Kerr, 2010; Acemoglu, Akcigit, Bloom, and William, 2011). However, rather than calibrating a structural model, our approach consists of building a measure of innovation implied by the model, and using that measure to test the model's predictions directly.

Our work is closely related to the literature in macroeconomics that aims to measure technological progress. Broadly, there are three main approaches to identifying technology shocks. The first two approaches measure technology shocks indirectly. One approach is to measure technological change –both at the aggregate and at the firm level – through TFP (see e.g. Olley and Pakes, 1996; Basu, Fernald, and Kimball, 2006). However, since these measures are based on residuals, they can incorporate other forces not directly related to technology, such as resource misallocation (see e.g., Hsieh and Klenow, 2009). Further, the productivity literature has documented substantial dispersion in measured productivity across plants and firms (see e.g., Syverson, 2004). The causes of this productivity dispersion remain a challenge (for a survey of recent work, see Syverson, 2011). We contribute to this literature by constructing a direct measure of technological innovation and showing that it can account for a significant fraction of cross-firm dispersion in measured TFP in our sample.

Second, researchers have imposed model-based restrictions to identify technology shocks either through VARs or through estimation of structural models (see e.g., Gali, 1999; Smets and Wouters, 2003). The resulting technology series are highly dependent on specific identification assumptions. Recent work in this area (e.g. Fisher, 2006; Justiniano, Primiceri, and Tambalotti, 2010, 2011) typically assigns an important role for embodied technical change for economic growth. We complement this literature by constructing a direct measure of embodied technical change and tracing its effects on both firm-level and aggregate outcomes.

Our work 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; Hall and Ziedonis, 2001). As a result, a larger number of patents does not necessarily imply greater technological innovation. Using R&D spending to measure innovation overcomes some of these issues, but doing so measures innovation indirectly. The link between inputs and output may vary as the efficiency of the research sector varies over time or due to other economic forces (see e.g., Kortum, 1993). The measure proposed by Alexopoulos (2011) based on books published in the field of technology overcomes many of these shortcomings. However, this measure is only available at the aggregate level, and 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 approach to measuring patent quality has several advantages over the existing approach that relies on patent citations. The innovation literature has documented that forward patent citations are informative about the intrinsic quality of patents (Harhoff, Narin, Scherer, and Vopel, 1999; Hall, Jaffe, and Trajtenberg, 2005; Moser, Ohmstedt, and Rhode, 2011). However, their use as a measure of innovation is subject to two significant limitations. First, counting the number of future citations to each patent requires information over the entire sample. In many economic applications – such as exploring the short- and medium-run response of investment or hiring decisions to innovation – it is desirable to use a measure based on the contemporaneous 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.[3] This lack of information creates problems in assessing the quality of earlier patents, since patents often tend to cite only the most recent ones (Caballero and Jaffe, 1993).[4] In

[3] Moser and Nicholas (2004) and Nicholas (2008) discuss issues in extracting citations data from patent documents before 1975. In addition, even in the post-1975 period, citation outcomes are affected by the identity of the patent examiner (Cockburn, Kortum, and Stern, 2002).

[4] The first year that patent citations are officially included on patent documents is 1947. Since patents are likely to cite only the latest patents, earlier patents will have lower citation counts. For instance, the

contrast, our measure is reliably available over a long time period. Indeed, when we repeat our empirical analysis weighting patents by citations rather than stock market reactions, we obtain similar qualitative effects, though the magnitudes are smaller by a factor of five to ten. Despite these two drawbacks, patent citations provide a valuable independent measure of the *realized* value of a patent. We therefore use patent citations as a validation of our procedure.

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 between patents and the stock market rate of return in a sample of 120 firms during the 1968–1975 period. His estimates imply that, on average, an unexpected arrival of one patent is associated with an increase in the firm's market value of $810,000. The ultimate objective of these papers is to measure the economic value of patents; in contrast, we use the stock market reaction as a means to an end—to construct appropriate weights for an innovation measure which we 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. Related to our paper is the work of Bloom, Schankerman, and Van 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.

I The Model

We start by developing a tractable general equilibrium model that serves to guide the empirical work in the following sections. Specifically, our model links the quality of a firm's innovative activity – measured through patents – to its stock market value. In addition, it allows us to extract improvements in the aggregate technology frontier by an aggregated response to successful patent grants. Since patentable innovation is embodied in new goods

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

or processes, in the remainder of our analysis we will use the terms innovation and embodied shock interchangeably.

I.A Setup

We consider an economy with a continuum of intermediate goods. There is a fixed set of intermediate goods indexed by j on the interval $[0,1]$. Each intermediate good j can by potentially offered in different vintages indexed by k_j. A representative firm produces the numeraire consumption good using intermediate goods and labor L^F according to

$$Y_t = A_t \left(L_t^F\right)^{1-\alpha} \int_0^1 \left(\sum_{k=-1}^{K_{jt}} \theta_{jk}^{\frac{1-\alpha}{\alpha}} q_{jkt} \right)^{\alpha} dj. \tag{1}$$

Here, θ_{jk} represents the quality of an intermediate good of line j and vintage k; K_{jt} represents the leading vintage of good j at time t; and q_{jkt} represents the produced quantity of vintage k of intermediate good j at time t. Last, A_t is a disembodied productivity shock whose growth rate is identically and independently distributed (IID) over time.

We model technological growth as an improvement in quality among the lines of intermediate goods by building on the model of Grossman and Helpman (1991). Each period, the technological frontier for good j advances forward with probability $\lambda_{jt} = \lambda_t$, where λ_t is common to all lines of intermediate goods. The rate at which the frontier expands over time, λ_t is the embodied technology shock in our model. For simplicity, we assume that λ_t is IID over time with mean $\overline{\lambda}$, and is independent of all other shocks in the model. Conditional on successful technological innovation at time, the leading quality of intermediate good j advances by a proportional factor $\chi_{jk} > 1$

$$\theta_{jk} = \chi_{jk}\, \theta_{jk-1}. \tag{2}$$

The magnitude of the quality improvement in each line of goods is stochastic and is identically and independently distributed with mean $\bar{\chi}$ and cdf given by F^{χ}.

There is a fixed set of firms $f \in [0, F]$, $F > 1$, that produce intermediate goods at a unit labor cost, $q_{jkt} = l_{jkt}$. Each new vintage created during period t is initially assigned randomly to one of the firms, so that each firm receives at most one new vintage and any firm is equally likely to receive any of the new vintages of intermediate goods. Thus, each firm is assigned a single new intermediate good vintage with probability λ_t/F.

If a firm is assigned a new intermediate good vintage, it immediately files for patent protection. The probability that a patent is granted, ν_{kj}, is itself random and IID with mean $\overline{\nu}$. We allow the probability of a patent grant to be correlated with the magnitude of the quality improvement, χ_{jk}. After the outcome of the patent application is decided, period-t production takes place. If the patent for vintage k of good j is granted to the firm, the firm gains the exclusive right to produce this vintage in perpetuity.We denote as Δ^{+}_{jft} an indicator function that takes the value one if firm f obtains the right to a leading quality vintage of good j at time t, and by Δ^{-}_{jft} if the firm loses its leading position to another firm.

The firm in possession of the patent on the leading quality vintage engages in Bertrand competition with the producers of all previous quality vintages of the same good. As in Grossman and Helpman (1991), the price for the leading vintage of good j at time t in equilibrium equals

$$p^{m}_{jt} = \chi_{jK_{jt}}^{\frac{1-\alpha}{\alpha}} w_t, \tag{3}$$

where w_t is the equilibrium market wage. At this price (3), only the firm in possession of the patent on the leading vintage K_{jt} engages in production of good j, and none of the earlier vintages are produced in equilibrium. If the patent for the latest vintage of good j is denied, all firms have access to the latest vintage. In this case, the market for good j is perfectly competitive, only the latest vintage is produced at price $p^{c}_{jt} = w_t$, and thus producing firms make zero profits from good j. In this case, we assume that all firms produce an equal amount of the non-patent protected goods.

Closing the model, there is an infinitely-lived representative household that supplies a unit of labor inelastically. The household faces a complete set of state-contingent securities and trades in financial markets to maximize life-time utility of consumption. The household's preferences are

$$\mathrm{E}_0 \left[\sum_{t=0}^{\infty} \rho^t \log C_t \right]. \tag{4}$$

I.B Equilibrium

Aggregate output is given by

$$Y_t = B_1 \, A_t \, \hat{\theta}_t^{1-\alpha} \tag{5}$$

and is a function of the average *second-best* level of technology available at time t,

$$\hat{\theta}_t \equiv \int_0^1 \theta_{j,K_{jt}-1} dj, \tag{6}$$

whose growth rate is IID and depends on the rate of improvement in the technology frontier, λ_t,

$$\hat{\theta}_t = (1 + (\bar{\chi} - 1) \, \lambda_t) \; \hat{\theta}_{t-1}. \tag{7}$$

If a patent for the latest vintage of good j is issued to a firm, that firm acts as a temporary monopolist. As long as it maintains the lead in product j, it obtains a per-period profit flow of

$$\pi_{jt}^m = \left(p_{jt}^m - w_t\right) q_{jt}^m = B_2 \, Y_t \, \left(1 - \chi_{jK_{jt}}^{1-\frac{1}{\alpha}}\right) \frac{\theta_{jK_{jt}-1}}{\hat{\theta}_t} \tag{8}$$

where B_5 is a constant. Following a successful patent application, the stock market value of the firm increases by the present value of these profits (8) – provided the firm maintains the lead – discounted using the household's intertemporal marginal rate of substitution:

$$\Theta_{jt} = B_3 \, Y_t \, \left(1 - \chi_{jK_{jt}}^{1-\frac{1}{\alpha}}\right) \frac{\theta_{jK_{jt}-1}}{\hat{\theta}_t}. \tag{9}$$

Examining (9), we see that the market value of the patent for the latest vintage of good j is increasing in the magnitude of the technological improvement $\chi_{jK_{jt}}$ over the previous vintage – which determines the firm's profit margin – and the quality level of the previous vintage $\theta_{jK_{jt}-1}$ – which determines the scale. Since both of these objects determine the firms' profitability, we use the notation $\tilde{\theta}_{jK_{jt}} \equiv \left(1 - \chi_{jK_{jt}}^{1-\frac{1}{\alpha}}\right) \theta_{jK_{jt}-1}$ to refer to the market value of the latest vintage. Here, note that even though the market and the social value of the patent are different because of the monopoly distortion – the social value is proportional to $\theta_{jK_{jt}}$ – they are related by $\tilde{\theta}_{jK_{jt}} = \theta_{jK_{jt}} \left(\chi_{K_{jt}}^{-1} - \chi_{K_{jt}}^{-1/\alpha} \right)$.

Conversely, if the patent application is declined, production of the leading vintage of the good is competitive. Hence all firms make zero profits.

Aggregating the gain in market value across firms with successful patent applications in period t and scaling by the capitalization of the market portfolio, P_t, yields

$$\frac{1}{P_t} \int_F \int_0^1 \Theta_{jt} \, \Delta^+_{jft} \, dj \, df = B_4 \, \lambda_t. \tag{10}$$

Equation (38) illustrates that the change in the aggregate market value observed upon successful patent applications is increasing in the embodied technology shock λ_t. Note, that this aggregated market reaction is informative about the average level of embodied technological progress *because* of patent protection. Even though patents serve only to restrict competition and limit output, in the absence of patent protection all firms make zero profits. Thus, the existence of patent protection allows us to infer the value of new innovations from stock market reactions.

II Construction of the innovation measure

In this section, we construct an empirical measure of the economic importance of each innovation, $\tilde{\theta}_j$, combining information from patent data and the stock market. The goal of doing so is twofold. First, constructing a measure of innovation that adjusts for the quality of each patent allows us to examine the model's predictions. Second, even though we use the model as a guide in constructing our measure, the main idea is robust to the specific details of the model. Hence, we expect such a measure to be more broadly useful.

Our main empirical challenge is to isolate the market's reaction to the patent Θ_t from other events that might affect stock market value. We will proceed in several steps. First, we isolate the release of information to the market. In particular, will exploit the publication of patent issuances by the USPTO. The patent office has consistently publicized successful patent applications throughout our sample, and this event allows us to isolate a discrete change in the information set of the market participants. However, even during this narrow window, stock prices are likely to be contaminated with other sources of news unrelated to the value of the patent. Therefore, our second step is to filter the stock return component from the realized stock return. Doing so requires us to estimate the signal to noise ratio in announcement window returns. We do so by comparing the volatility of stock returns on the days with announcements to the days without announcements. Next, we describe these steps in more detail.

II.A Data description

Here, we provide a brief description of the patent data and relegate the details to the Online Appendix. We download the entire history of U.S. patent documents (7.8 million patents) from Google Patents using an automation script.[5] First, we clean assignee names by comparing each assignee name to the more common names, and if a given name is "close", in the sense of the Levenshtein distance, to a much more common name, we substitute the common name for the uncommon name. Having an assignee name for each patent, we match all patents in the Google data to corporations whose returns are in the CRSP database. Some of these patents appear in the NBER data set and therefore are already matched to CRSP firms. Remaining assignee names are matched to CRSP firm names using a name matching algorithm. Visual inspection of the matched names confirms very few mistakes in the matching. We extract patent citations from the Google data and complement them with the hand-collected reference data of Nicholas (2008).[6]

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

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

Out of the 6.2 million patents granted in or after 1926, we find the presence of an assignee in 4.4 million. After matching the names of the assignees to public firms in CRSP, we obtain a database of 1,915,031 million matched patents. Out of these patents, 523,301 (27%) are not included in the NBER data. 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 is comparable, even though we use only data extracted from OCR documents for the period before the NBER data. Last, another point of comparison is Nicholas (2008), who uses hand-collected patent data covering 1910 to 1939. From 1926–1929, he matches 9,707 patents, while our database includes 8,858 patents; from 1930–1939 he has 32,778 patents while our database includes 47,036 matches during this period.

II.B Identifying Information Events

The first step in constructing our measure is to we isolate the release of information to the market. The USPTO's publication, *Official Gazette*, which is published every Tuesday, lists patents that are issued that day and reports details of the patent. Our model links the stock market reaction on the day the patent is granted to the total market value by

$$\Delta V_{jt}^{g} = \Theta_{jt}\,(1 - \nu_{jk}), \tag{11}$$

where ν_{jk} is the ex-ante probability that the patent application is successful. For know, we assume that the market value of the patent Θ_j is perfectly observable to market participants before the patent is granted. We show how relaxing this assumption affects our results in Section II.F.

Examining equation (11), we see that it *understates* the total impact of the patent on the firm value by a factor of v_j, since the information about the patent allocation is known to the market before the patent application is resolved. Pinpointing the exact timing of the information release prior to the grant date is difficult, since prior to 2000, patent application

appear near any potential patent number, it is unlikely that we would incorrectly record a patent citation – it is far more likely that we would fail to record a citation than record one that isn't there.

filings were not publicized (see, e.g., Austin, 1993). However, subsequent to the American Inventors Protection Act, which became effective on November 30, 2000, the USPTO 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.

Hence, when application publication dates are available, we can also study the stock market reaction on the day the application is published. Assuming that the application was kept secret until that date, after the market learns that firm f has applied for a patent for good j in period t, but prior to the patent decision being made, the market value of the firm increases by

$$\log \Delta V_{jt}^{p} = \Theta_{jt}\, \nu_{kj}. \tag{12}$$

Next, we assess if information is revealed on patent grant dates by investigating whether stock prices behave differently on days patents are granted than when they are not. First, in Table 1, we document that trading volume increases around the days that patents are granted (or their applications are published). In particular, we regress a firm's share turnover T (trading volume divided by shares outstanding) on an announcement day dummy variable I_{fd},

$$T_{fd+k} = a_0 + a_{ft} + b_d + b(k)\, I_{fd} + u_{fd}, \tag{13}$$

controlling for firm-year a_{ft} and day-of-week b_d fixed effects. The results show that, as we vary k from -1 to 5, there is a statistically significant increase in share turnover around the day that the firm is granted a patent or its application is publicized. Specifically, volume increases on the day of the announcement, and remains temporarily higher for the next two days. We find that the total turnover in the first three days after the announcement increases by 0.16%. Given that the daily median turnover rate is 1.29%, this is an economically significant increase in trading volume, and supports the view that patent issuance conveys important information to the market.[7] Last, our estimates imply that trading volume is temporarily lower prior to the announcement, possibly due to the presence of increased information asymmetry.

[7] 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.

Last, we need to choose the length of the announcement window, l, to use for the remainder of our analysis. Varying the length of the window trades off potentially omitting useful information versus potentially adding noise to our estimates. We choose a three-day window ($l = 2$) and as a robustness test extend the window to five days ($l = 4$).

II.C Filtering the value of a patent

Here, we extract the component of firm return that is related to the patent value. 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. Our results are quantitatively similar when using this alternative definition.

The stock price of innovating firms may fluctuate for reasons unrelated to innovation during the announcement window. Hence, we construct a measure of innovation that explicitly accounts for measurement error.[8] In particular, we decompose the idiosyncratic stock return r around the time that patent j is announced as

$$r_j^l = x_j + \varepsilon_{jl}, \tag{14}$$

where x_j denotes the value of patent j as a fraction of the firm's market capitalization; l denotes the length of the event window we use to compute returns and ε_{jl} denotes the component of the firm's stock return that is unrelated to the patent.

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

We construct the conditional expectation of the dollar value of patent j as

$$\begin{aligned}\widehat{\Theta}_j^i &= \widehat{\Delta V_{jt}^i} \\ &= \frac{1}{N} E[x_j | r_{jd}^l] \ P_{jd-1},\end{aligned} \tag{15}$$

where $i \in \{p, g\}$ denotes grant or publication date, and P_{jd-1} is the market capitalization of the firm owning patent j on the day prior to the announcement. If multiple patents N are issued to the same firm on the same day, we assign each patent a fraction $1/N$ of the total value.

To recover the value of the patent, we need to make assumptions about the joint distribution of x and ε. Following our model – equation (9) – the value of the patent x is a positive random variable. Hence, we assume that x is distributed according to a Gaussian $\mathcal{N}(0, \sigma_{vj}^2)$ truncated at zero. Further, we assume that the noise term is normally distributed, $\varepsilon_{jl} \sim \mathcal{N}(0, \sigma_{\xi j}^2)$. Last, there is strong evidence that idiosyncratic return volatility varies both in the time-series and the cross-section. Hence, we allow both $\sigma_{\xi j}^2$ and σ_{vj}^2 to vary at across firms and across time, but in constant proportions. We do this in order to reduce the number of parameters we estimate.[9] We estimate these variances non-parametrically using $l-$day returns at the firm-year level.

The filtered value of x_j as a function of the stock return is equal to

$$E[x_j | r_j^l] = \delta_j \, r_j^l + \sqrt{\delta_j} \, \sigma_{\xi j} \, \frac{\phi(R_j)}{1 - \Phi(R_j)}, \tag{16}$$

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

$$R_j = -\sqrt{\delta_j} \, \frac{r_j^l}{\sigma_{\xi j}}, \qquad \delta_j = \frac{\sigma_{vj}^2}{\sigma_{vj}^2 + \sigma_{\xi j}^2}. \tag{17}$$

[9] Our specification of the distribution of x_j relaxes the assumption that θ_j is identically distributed among intermediate goods we made in Section I. Doing so simplifies the empirical analysis but does not alter the main implications of the model.

The conditional value of a patent in equation (16) is an increasing and convex function of the daily firm return.

Our assumption that $\sigma^2_{\xi j}$ and σ^2_{vj} vary in constant proportions implies that the signal-to-noise ratio is constant across firms and time, $\delta_j = \delta$. To estimate δ, we compute the increase in the volatility of firm returns around patent announcement days. Specifically, we regress log squared returns on a patent announcement-day dummy variable, I_{fd},

$$\log \left(r^l_{fd}\right)^2 = a_0 + a_{ft} + b_d + \gamma I_{fd} + u_{fd}, \tag{18}$$

where r^l_{fd} refers to the idiosyncratic return of firm f centered on day d with window of length l. We control for firm-year (a_{ft}) and day-of-week (b_d) fixed effects. Taking into account the adjustment for the variance of the truncated normal, the signal-to-noise estimate can be recovered from our estimate γ by

$$\widehat{\delta} = 1 - \left(1 + \frac{1}{1 - \left(\frac{\phi(0)}{1-\Phi(0)}\right)^2} \left(e^{\widehat{\gamma}} - 1\right)\right)^{-1}. \tag{19}$$

We estimate (18) using a three-day ($l = 2$) and a five-day ($l = 4$) return announcement window. Our estimates imply $\widehat{\delta} \approx 0.04$ in both cases, so we use this as our benchmark value.[10]

Last, we estimate the variance of the measurement error $\sigma^2_{\xi j}$. 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 σ^2_v and σ^2_ξ. Given the estimate of the daily variance σ^2_{ft}, the fraction of trading days that are announcement days, μ, and our estimate $\widehat{\gamma}$, we recover the measurement error by $\sigma^2_{\xi ft} = \sigma^2_{ft}\,(1 + l)\,\left(1 + \mu_{ft}(1 + l)\frac{\widehat{\gamma}}{1-\widehat{\gamma}}\right)^{-1}$.

In Table 2 we report the distribution of number of patents granted per day, idiosyncratic firm returns r_f, filtered values $E[x_j|r_f]$ and dollar values A in 1982 dollars – using the CPI deflator – across our sample. To conserve space, we focus only on patent grant dates and a window of 3 days. We see that distribution of firm returns is rightly skewed, and positive

[10] As a robustness test, we estimate equation (18) allowing the signal-to-noise ratio δ to vary across firm size or volatility quintiles. We find no meaningful differences in the estimates of δ across quintiles.

roughly 55 percent of the time. Our measure implies that the median value of a patent is \$2.2 million, which is comparable to the findings of Harhoff, Scherer, and Vopel (2003) and Giuri et al. (2007) who report the distribution of valuations for small samples of European patents based on survey responses.

Equation (16) implies that negative returns are interpreted as small values for the patent, while positive returns are interpreted as larger positive values. This convex behavior stems from our assumption that the value of a patent x_j in equation (14) is non-negative, which follows from equation (9). One worry is that because $\widehat{\Theta}_j$ is a convex function of the idiosyncratic return r^l_{jd}, it is influenced by the firm's volatility. Hence, as a robustness check, we include the firm's idiosyncratic volatility as a control throughout our empirical analysis. Last, to assess the benefit of explicitly recognizing the non-negativity of x_j in our estimation of the patent value, we estimate an alternative measure where we assume that $x_j \sim \mathcal{N}(0, \sigma^2_{vj})$, with no truncation at zero. We then follow equation (15) and construct a second measure of patent values $\overline{\Theta}$, which is equal to the total dollar change in stock market value around the issue of patent, ΔV^{grant}, multiplied by our estimate of γ.

II.D Evidence validating our innovation measure

Prior to using our measure for empirical work, we provide evidence that it is correlated with a measure of the *realized* value of a patent. In particular, we follow the literature studying innovation that concludes that the number of times that patents are cited in the future is correlated with the quality of the patent (Harhoff et al., 1999; Hall et al., 2005; Moser et al., 2011). Accordingly, this section uses the number of citations a patent receives in the future as a measure of its realized value.

Patent citations

The empirical literature typically uses patent citations as an empirical measure of the value of a patent. We relate the total number of citations the patent receives in the future

N_j to our innovation measure $\widehat{\Theta}_j$

$$\log(1 + N_j) = a + b \log \widehat{\Theta}^i_j + c\, Z_j + u_j. \tag{20}$$

As we can infer from (9) and (11), the stock market reaction to a firm being issued a patent is a noisy measure of patent quality, since it is influenced by idiosyncratic factors – the likelihood of patent approval v_j – as well as general equilibrium effects. The model also likely omits other factors than may influence citations. To control for omitted variables, we include a vector of controls Z that includes grant-year (or publication-year) fixed effects because older patents have had more time to accumulate citations; the firm's log idiosyncratic volatility to control for its possible effect on our innovation measure; the firm's log market capitalization, as larger firms may produce more influential patents; the log number of patents N granted to the same firm on the same day, since it mechanically affects our measure; firm fixed effects to control for the presence of unobservable firm effects on citations and our innovation measure; and technology class-year fixed effects, since citation numbers may vary by industry. As our baseline case, we consider three-day ($l = 2$) announcement day windows. We cluster the standard errors by grant or publication year and present the results with different versions of controls in Table 3.

In panel A, we see that our innovation measure $\widehat{\Theta}$ constructed using the patent-issuance window is related to the number of future citations across specifications. The economic magnitudes are substantial. The median number of citations a patent receives is 5. Our point estimates imply that an increase from the median to the 90th percentile in terms of our innovation measure $\widehat{\Theta}$ – corresponding to an increase of approximately 23 million 1982 US dollars – is associated with a 9 to 54 percent proportional increase in the number of future citations.[11]

Following the American Inventors Protection Act of 2000 , patent applications were published. We focus on the stock market reaction around the three-day window that firm's

[11]Note that small changes in citations generated by a patent can be associated with large value implications for the firm producing the patent. For instance, Hall et al. (2005) show that 1 more citation per patent (around the median cites per patent) is associated with 3 percent higher market value for the firm that produces the patent.

application is published in Panel B. We find that the economic magnitudes are smaller, ranging from 4 to 11 percent per 90th to 50th percentile change in $\widehat{\Theta}$ and not statistically significant once we include firm effects in the specification. These findings suggest that the information content on this event may be small, perhaps because the market is already informed about the patent application. These results are consistent with our findings in Section II.F below.

We perform several robustness tests to our specification (20). For brevity, we only report the results of these tests and refer the interested reader to the Online Appendix. First, we estimate a semi-log specification, replacing $\log(1+N)$ with N. Doing so leads to economically similar estimates. Second, we repeat the exercise extending the announcement window to five-days ($l = 4$). In this case our results are quantitatively similar. Last, we document the relation between our measure of the raw change in stock market value $\overline{\theta} \propto \Delta V^{grant}$ and the future number of citations. The results are substantially weaker: the point estimates are positive, but there is no statistically significant relation between the raw change in stock market value $\overline{\theta}$ and the number of citations the patent receives in the future. We interpret this finding as evidence that the stock market reaction contains significant noise, and that our assumption that the value of a patent is weakly positive is crucial in disentangling the information contained in returns from components unrelated to the value of the patent.

Placebo tests

Our findings in Section II.D could be influenced by unobservable, time-varying effects at the firm level, that affect both the movements in the stock price of the firm as well as the number of citations that patents assigned to it receives. To address this concern, we perform a series of placebo tests to illustrate that the relation between stock market reaction to a particular patent and the number of citations received by that patent in the future is not spurious. In each placebo experiment, we randomly generate a different issue date for each patent within the same year the patent is granted to the firm. We reconstruct our measure using the placebo grant dates and estimate (20). We repeat this exercise 500 times. To conserve space, we report the results of placebo tests corresponding only to the specification in the first row, fourth column of Table 3.

Figure 2 reports the distribution of estimate $\widehat{b}$ across the placebo tests. The coefficient $\widehat{b}$ ranges from -0.01 to 0.001 across replications, substantially different from our point estimate of 0.054. This analysis suggests that the relation between the stock market response to a patent being granted and the number of citations the patent receives in the future is unlikely to be spurious.

II.E 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 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 1, the stock price increased 67 percent (in excess of market returns) in the three days following the patent announcement. Investors clearly believed the patent was valuable, and news of the patent was reported in the media. For example, on August 8 *Business Wire* quoted the biotechnology head of a Washington-based patent law firm as saying "The claims issued to Genex will dominate the whole industry. Companies wishing to make, use or sell genetically engineered SCA proteins will have to negotiate with Genex for the rights to do so."

The patent has subsequently proved to be important on other dimensions as well. The research that developed the patent, Bird, Hardman, Jacobson, Johnson, Kaufman, Lee, Lee, Pope, Riordan, and Whitlow (1988), was published in *Science* and has since been cited over 1300 times,[12] while the patent itself has been subsequently cited by 775 patents. Genex was acquired in 1991 by another biotechnology firm, Enzon. News reports at the time indicate that the acquisition was made in particular to give Enzon access to Genex's protein technology.

[12] Google Scholar citation count.

Another example from the biotechnology industry is patent 5,585,089, granted to Protein Design Labs on December 17, 1996. The stock rose 22 percent in the next two days on especially high trading volume (Panel B of Figure 1). 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 percent in the two days after the announcement, adding $900 million in market capitalization (see Panel C of Figure 1).

II.F Effect of imperfect information about patents

Our operating assumption so far has been that the market does not revise its beliefs about the value of the patent at the time the patent is granted. This is because, in our model, the information content of the patent is perfectly anticipated by the market.[13] This assumption is valid post-2000, when the American Inventors Protection Act required that patent applications be publicly available before the patent is granted. In contrast, prior to 2000, patent applications were only disclosed to the public at the time the patent is granted to the firm. Hence, during this period, it is possible that the market did not know the full value of the patent prior to the patent being granted.

We now explore how the effect of imperfect information about patent quality impacts our empirical procedure. We introduce a small modification to the model in Section I, allowing for patent quality to be only imperfectly observable to the market prior to the patent being granted. Specifically, let

$$s_{jt} = \Theta_{jt} + e_{jt}, \tag{21}$$

[13]Alternatively, the assumption is consistent with information about the patent being fully unanticipated.

where e is a mean-zero random variable. The variable s is an imperfect but unbiased estimate of patent quality that is already incorporated into the firm's market value prior to the patent being granted. At the time of the patent grant, the true quality of the patent θ is revealed to the market. In this case, following a successful patent grant, the stock price of the firm changes by

$$\Delta V^{g}_{ft} = (1 - v_j)\ \Theta_{jt} - v_j\, e_{jt}. \tag{22}$$

Examining equation (22), the stock market reaction to the patent grant contains two components. The first part is positive, reflects the true value of the patent, and is the same as in the baseline model. The second part is proportional to the mean-zero random variable e that reflects the revision of market beliefs about the value of the patent.

The problem of extracting the value of the patent with imperfect information fits into the framework of equation (14) with one modification. Specifically, the noise term ε in equation (14) now includes movements in stock returns unrelated to the value of the patent *plus* the revision in market expectations e. Hence, we might need to revisit our estimation of the signal-to-noise ratio δ, since we may no longer be able to use the difference in the volatility of firm returns on patenting versus non-patenting days to infer the variance of noise.

We address this issue by assessing the nature of information about the quality of the patent released on grant days. Specifically, we exploit the change in information disclosure policy by the American Inventors Protection Act (AIPA) that applied to all patents filed after November 30th. For the patents that were filed after November 30th 2000, the market had full knowledge of their quality at the time these patents were granted. On the other hand, for the patents filed before November 30th, it is possible that on the grant day the stock market reaction indeed contains news about θ_j. We thus compare estimates of the signal-to-noise ratio across the two sets of patents: patents that were filed just before the act, that is in the month of November 2000; and patents that were filed immediately after the act, that is in December 2000.

We first establish that these patents are similar in terms of quality, by comparing the distribution of patent citations across the two groups. The Kolmogorov-Smirnov test fails to reject the null that the two distributions are the same at the 10 percent level. Next, we estimate the signal-to-noise ratio δ across these two sets of patents, allowing the coefficient on the grant in equation (18) to vary across the two groups. Even though the point estimate is 0.005 smaller for the patents filed in December 2000, the difference is not statistically significant (p-value is 0.29). As further supporting evidence that the market was already informed about the quality of the patents prior to the AIPA, we estimate equation (13) separately for each group of patents, and find no evidence that the response of trading volume on grant dates is systematically different across the two groups.

Overall, our results suggest that, prior to the enactment of AIPA, the market was as well informed about the value of the patent before the grant date as post-2000, when the patent document was in the public domain. These findings suggests that the variance of e may be small and as a result we do not have to alter the estimation of the signal-to-noise ratio from equation (14).[14]

III Innovation, reallocation and growth

In this section, we employ our innovation measure to examine the empirical predictions of our model. The goal is to provide evidence for the underlying main mechanisms in our model and in the process provide indirect support for the validity of our measure. The distinguishing feature of innovation is that it has a heterogeneous impact on the population of firms. Firms that successfully innovate clearly benefit. By contrast, firms that fail to innovate while the competitors do, fall behind in the technology race. Consistent with our model, we expect such firms to experience an outflow of resources and a subsequent drop in economic activity.

Before we conduct our analysis, a caveat is in order. 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

[14] Nevertheless, we also investigate the robustness of our results to different values of δ. In particular, in the presence of imperfect information about the patent, equation (22) shows that our estimate of the signal-to-noise ratio δ based on patenting versus non-patenting days might *underestimate* the amount of noise. We repeat our analysis relating patent citations to our innovation measure constructed using smaller estimates of δ ($\delta = 0.03$ and $\delta = 0.015$). Our results relating our measure of innovation to the number of citations a patent receives in the future remain very similar.

more important technology shocks.[15] This omission is likely to bias our findings toward zero. The magnitude of any bias, however, is likely to be small for two reasons. 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.

III.A Data Construction

Our model features two distinct shocks related to innovation. The realization of the first shock affects which firms innovate and climb the technology ladder in product j. From the aggregate perspective, this shock is idiosyncratic; the identity of which firms innovate does not affect the evolution of the technology frontier $\hat{\theta}$. The second shock, λ_t, determines the rate of technological progress. Our goal is to combine information from patents and stock returns to obtain measures of both shocks.

We merge the patent data with the CRSP/Compustat data. We restrict the sample to firm-year observations with non-missing values for book assets, PPE, employment, sales, operating income, and SIC classification codes. We omit financial firms (SIC codes 6000 to 6799) and utilities (SIC codes 4900 to 4949) leaving us with 152,080 firm-year observations that include 14,795 firms in the 1950 to 2010 period. We winsorize all variables by year at the 0.5% level.

Innovation by the firm

The first step in our firm-level analysis is to construct a measure of embodied technological change at the firm level. We construct our dollar measure of innovation at the firm level by aggregating the dollar values across all patents granted to firm f in year t,

$$\hat{\Xi}_{ft} = \sum_{j \in J^{\Delta}_{ft}} \widehat{\Theta}^{g}_{j}, \tag{23}$$

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

where J^{Δ}_{ft} denotes the set of issued patents to firm f in year t.[16]

However, our estimate of the dollar value of patents could be potentially affected by many factors, such as the scale of the firm or other shocks to profitability (for example, demand shocks or the disembodied shock A in the model). Hence, we divide the dollar value of innovation Ξ by the end-of-year firm market capitalization, P, in year t:

$$\xi_{ft} = \frac{\hat{\Xi}_{ft}}{P_{ft}}. \tag{24}$$

Our firm-level innovation measure ξ_f can be therefore interpreted as the fraction of firm f's value that can be attributed to innovation in year t.

For comparison, the construction of the same measure (24) in the model yields

$$\xi_{ft} = \frac{(1-\nu_j)\left(1-\chi_{jK_{jt}}^{1-\frac{1}{\alpha}}\right)\ \frac{\theta_{jtk-1}}{\hat{\theta}_t}}{\sum_{j'\in J_{ft}}\left(1-\chi_{j'K_{j't}}^{1-\frac{1}{\alpha}}\right)\ \frac{\theta_{j'tk-1}}{\hat{\theta}_t}+C_0}\Delta^+_{jt}, \tag{25}$$

where J_{ft} is the set of patents owned by firm f and C_0 is a constant capturing the net present value of future patents.

As we see from its model equivalent, the firm-level measure (24) provides an estimate of the firm's innovative activity relative to the technology frontier. It increases as the firm acquires a new patent (Δ^+), when that patent represents a bigger improvement relative to the frontier (χ_{jK}), and when the size of the market for the good is larger (θ_{jK-1}). Equation (24) is an underestimate of the economic value of the patent to firm f due to the fact that some of this information has been already priced in the market – captured by the $1-\nu_j$ term in parenthesis.

[16]Alternatively, we could also include the dollar market reaction during the period the patent application was published. We choose to not do so for two reasons. First, for most of our sample period, patent applications were kept secret until the patent was granted. Hence, if we were to include the reaction to patent publications for only part of the sample, the time-series properties of the measure would be different. Second, our analysis in the previous section suggests that the actual information release during the patent publication window is very small.

Innovation by the firm's competitors

Next, 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 P:

$$\xi_{I\setminus ft} = \sum_{h \in J_{It} \setminus \{f\}} \Xi_{ht} \Bigg/ \sum_{h \in J_{It} \setminus \{f\}} P_{ht}, \tag{26}$$

where J_{It} denotes the set of firms in industry I, defined according to 3-digit SIC codes.

Recall that the model does not feature separate industries. If we interpret the model as applying to a single industry, then the model equivalent of equation (26) is proportional to the embodied shock λ_t. However, if the rate of technological progress varies across industries in a systematic manner – there is some cross-sectional correlation in λ_{jt} within industries – then equation (26) would produce the average rate of technological progress at the industry level, λ_{It}, using an argument similar to (38). Since the rate of progress likely varies across different industries, we draw a distinction between the rate of technological progress in a specific industry, λ_{It}, and the aggregate rate of progress, λ_t.

Here, we should note that even though the firm-level market response to a successful patent grant (11) underestimates the market value of a patent Θ_j, the effect of this bias when aggregating across patents when constructing the empirical equivalent of (38) is a constant scaling factor that depends on the joint distribution of ν_j and Θ_j. See the Online Appendix for more details.

III.B Descriptive Statistics

Table 5 displays descriptive statistics for the firms in our sample. As we see, the distribution of innovation variables is heavily skewed. The number of patents, patent citations, and out firm-level measure ξ_{ft} are skewed to the right and have fat tails.[17] Given the skewness in these measures, when interpreting the output of the regression we compare movements from

[17]Specifically, restricting attention to the top 10 percent of the distribution, the relation between the log complementary empirical cdf, $\log(1 - F(A))$, and the log innovation measure, $\log A$ is close to linear, with a slope coefficient of -1.9.

the median to the 90-th percentile. The distribution of firm investment and hiring are also somewhat skewed, but substantially less so than our innovation measures.

Next, we relate our firm-level measure of innovation to firm characteristics, in particular Tobin's Q, firm size, K, and R&D expenditures to total assets

$$\xi_{ft} = a_0 + a_1 \log Q_{t-1} + a_2 \log K_{t-1} + a_3 \log RD_{t-1} + \rho\, \xi_{ft-1} + u_{ft}. \tag{27}$$

We estimate equation (27) using a Tobit model. Since information on R&D expenditure is reliably reported in Compustat only from 1975 onwards, our sample period for regressions that use R&D spending is restricted to 1975–2010. 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 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. See the Online Appendix for the full set of results.

III.C Reallocation

We start our analysis by exploring the extent to which innovation activity is associated with resource reallocation across firms. In our model, a firm's labor input choice depends on the number of product lines it operates. The percentage change in a firm's labor choice $g^l_{ft} = \Delta \log L_{ft}$ depends on the firm's own innovation activity, Δ^+, as well as the rate λ_t of technological progress in the economy. The growth rate in firm f's input use is

$$g^l_{ft} \approx \frac{\theta_{jK_{jt}-1}\, \chi_{jK_{jt}}^{1-\frac{1}{\alpha}}}{\sum_{j' \in J_{ft-1}} \theta_{j'K_{jt-1}-1}\, \chi_{j'K_{j't-1}}^{1-\frac{1}{\alpha}} + B_6}\, \Delta^+_{jt} - \lambda_{It}\, \phi_{ft-1} - \log \frac{\hat{\theta}_t}{\hat{\theta}_{t-1}}, \tag{28}$$

where ϕ_{ft-1} is the share of patent-protected goods in firm f's production (recall that all firms produce the non-patent protected goods at equal amounts). Examining equation (28), we see that labor use by firm f varies over time as (i) the firm acquires patents for new products; (ii) the firm loses a good to another firm; and (iii) as factor prices change due to changes in the aggregate frontier $\hat{\theta}$. These three effects correspond, in the same order, to the three terms in equation (28).[18] Comparing (28) to (25), we see that both our firm-level innovation measure and the increase in labor demand are increasing in the fact the firm is granted a patent, Δ^+, and on the scale of the previous invention, $\theta_{jK_{jt}-1}$. By contrast, a larger improvement in quality over the previous invention χ leads to a higher market value for the patent but a lower level of equilibrium output due to the monopoly distortion.

We make two departures from equation (28) when taking the model to the data. First, we consider both capital and labor inputs. Even though the model does not feature physical capital, examining a firm's capital choice is a natural extension. Second, adjusting capital and labor inputs may involve some delay, especially for physical capital. Hence, we consider the growth rate in capital and labor inputs over multiple horizons, τ. We estimate the following specification,

$$g^i_{ft,t+\tau} = a_i(\tau)\,\xi_{ft} + b_i(\tau)\,\xi_{I\setminus ft} + \gamma_t + d_I + c\,Z_{ft} + u_{ft+\tau}, \tag{29}$$

where $i = [k, l]$ indexes the firm's capital and labor choice, $g^i_{ft,t+\tau}$ is the annualized net growth rate between t and $t+\tau$. We include industry (d_I) and time (γ_t) dummies in all specifications. We cluster the standard errors by firm.

Our main coefficients of interest are a and b, which capture the change in factor inputs following innovation by the firm ξ_f and its competitors $\xi_{I\setminus f}$, respectively. The time dummies γ_t absorb changes in factor prices at the aggregate level.

We control for several firm characteristics Z. First, as we see from equation (28), scaling by firm size may introduce some mechanical correlation between the dependent variable and our innovation measure – since large firms innovate more; hence, we control for the log

[18] In obtaining (28), we have aggregated over the firm's competitors, hence the chance that the firm loses the lead is proportional to λ_{It}.

value of the capital stock or number of employees. Second, we control for firm idiosyncratic volatility σ_{ft} to account for its possible effect on our innovation measure due tot he fact it is a convex transformation of returns. Third, we control for firm profitability, since firms experiencing a positive shock to profitability may have higher propensity to innovate. Last, we include one lag of the dependent variable $g^i_{ft-1,t}$, since inputs may be slow to adjust. We present results adding these controls sequentially.

As we see in Tables 6, firm innovation is associated with a substantial increase in its capital and labor inputs. The estimated coefficients a are statistically significant across specifications. The economic significance is stronger for labor than for capital, and in both cases increases with the horizon. Depending on controls, an increase in innovation by the firm from the 50th to the 90th percentile leads to an increase in the capital growth rate by 0.6% to 1.1% – compared to a median one-year growth rate of 8.8% – at the one-year horizon, and an increase of 1.8% to 2.3% per year over three years. For labor, the corresponding one-year and three-year increase is 0.2% to 0.6% , and 0.9% to 1.1%, respectively, compared to the sample median of 2.3%. Importantly, the point estimates of b imply a substantial reallocation of resources towards firms that innovate away from those that do not. An increase in the level of innovation by the firm's competitors form the median to the 90-th percentile is associated with a declining in the firm's capital growth by 2.3% to 2.6% after one year; this negative effect increases to 4% to 4.5% per year over three years. For labor, the corresponding one-year estimates are 1.7% to 1.9%, and are fairly constant across horizons.

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. A natural question is what is the overall effect of the average level of economic activity to aggregate changes in the capital and labor stock – new investment and job creation – as well as the degree of capital and labor reallocation. Comparing the estimated coefficients a and b across specifications is not sufficient; since we are estimating specifications using growth rates, the relative size of the firms that innovate plays a role. To this end, we first compute the growth rate in firm f's choice of input i between time t and τ that can be attributed to innovation, $\hat{g}^i_{ft,t+\tau} \equiv \hat{a}_i(\tau)\,\xi_{ft} + \hat{b}_i(\tau)\,\xi_{I\setminus ft}$. We then aggregate across firms to compute the aggregate change in the capital and labor stock C that can be attributed to innovation,

$$\widehat{C}^k_{t,\tau} = \frac{\sum_f \hat{g}^k_{ft,t+\tau} K_{ft}}{\sum_f K_{ft}}, \qquad \widehat{C}^l_{t,\tau} = \frac{\sum_f \hat{g}^l_{ft,t+\tau} L_t}{\sum_f L_{ft}}, \tag{30}$$

where $\hat{g}^i_{ft,t+\tau} \equiv \hat{a}_i(\tau)\,\xi_{ft} + \hat{b}_i(\tau)\,\xi_{I\setminus ft}$ is the growth rate in firm f's choice of input i between time t and τ that can be attributed to innovation. In addition we construct a measure of excess capital and job reallocation R

$$\widehat{R}^k_{t,\tau} = \frac{\sum_f |\hat{g}^k_{ft,t+\tau}| K_{ft}}{\sum_f K_{ft}} - \widehat{C}^k_t, \qquad \widehat{R}^l_{t,\tau} = \frac{\sum_f |\hat{g}^l_{ft,t+\tau}| L_t}{\sum_f L_{ft}} - \widehat{C}^l_t \tag{31}$$

in line with Davis, Haltiwanger, and Schuh (1998), where we interpret negative growth rates attributed to innovation as capital sales or labor firings. For comparison, we also compute average turnover rates for capital and labor as $\bar{R}^k_t = \frac{\sum_f |\Delta K_{ft}|}{\sum_f K_{ft}} - \bar{C}^k_t$ and $\bar{R}^l_t = \frac{\sum_f |\Delta L_{ft}|}{\sum_f L_{ft}} - \bar{C}^l_t$, respectively, where $\bar{C}^i_t$ denotes the net increase in the aggregate capital or labor stock among the firms in our sample.

We find that innovation is associated with substantial capital and labor reallocation, while the effect on new capital formation and job creation is rather small. At horizons of one to three years, innovation accounts for an average annualized growth rate of 0.14% to 0.34% in the aggregate capital stock , which accounts for less than 5% of the mean aggregate growth rate of 8.7% among the firms in our sample. Regarding the net increase in firm labor demand, the contribution of innovation is somewhat higher: the mean hiring rate that can be attributed to innovation ranges from -0.1% to 0.25% , which accounts for up to 10% of the mean growth of employment of for the firms in our sample. Further, these estimates need to be interpreted with caution, since they are based on a sample of continuing firms. As we see below, once we take into account exits, the effect of innovation on job creation is unlikely to be positive. By contrast, the contribution of innovation in the aggregate reallocation activity is substantial, especially for capital. Our estimates $\hat{R}^i_t$ imply that average innovation-associated capital and labor turnover range from 0.8% to 1.2% and 0.3% to 0.4% across horizons, respectively. For comparison, the overall mean turnover rate for capital and labor ranges from 1.6% to 2.4% and 3.5% to 5.5% across horizons, respectively.

Last, a natural question is what is the additional information contained in our innovation measure relative to using the number of citation-weighted patents granted to the firm in year t. In contrast to our measure, citations contain information not available to economic actors at the time that production and allocation decisions are made. As before, we measure innovation ξ_{ft} as the number of patents granted to firm f in year t, and construct $\xi_{I\setminus ft}$ as the average number of patents granted to other firms in the same industry in the same year. We estimate equation (29) for capital and labor growth. We find qualitatively similar results as our innovation measure, but the magnitudes are smaller by a factor of five. We report the full set of results in the online Appendix.

III.D Firm Exit

An important component of reallocation is firm exit. Hence, we next relate the likelihood that a firm exits the industry as a function of its innovative activity and its competitors. In our model, the probability that a firm loses all its product lines at time t, and thus exits the economy, is

$$Prob(Exit_{ft}) = (\lambda_t)^{n_{ft}} \left(1 - \frac{\overline{\nu}\lambda_t}{F}\right), \tag{32}$$

where n_{ft} is the number of product lines the firm operates under patent protection. Examining equation (33), we see that the probability that the firm exits the industry is decreasing in its own innovation and increasing in the innovative activity of it's competitors. Moreover, both effects are larger for smaller firms, that is, firms with fewer product lines n.

We estimate the equivalent of equation (33) in the data using a logit model,

$$Prob(Exit_{ft}) = f(a\,\xi_{ft} + b\,\xi_{I\setminus ft}). \tag{33}$$

We define exits as firm liquidation based on CRSP delisting codes, specifically when the first digit of CRSP dlstcd is equal to 4. We have 209 such events in our sample, corresponding to 1.4% of the firms and 0.13% of the firm-year observations in our sample. We cluster the errors by firm. We report results with and without time dummies. We report marginal effects of each variable evaluated at their respective medians, and compute the standard errors using the delta method.

We present the results in Table 7. As we see in columns (1) and (2), increased innovation by the firm is associated with a lower probability of firm exit. An increase in firm innovation from the median to the 90-th percentile is associated with a reduction of 0.40% to 0.67% to the probability of firm exit; these magntidues are economically significant compared to the unconditional probability of exit which is equal to 0.13%. Conversely, high innovation by competing firms leads to increased likelihood of exit. An increase in competitor innovation from the median to the 90-th percentile is associated with a 0.02% to 0.04% increase in the likelihood of firm exit, compared to the unconditional probability of 0.13%.

Our model implies that both of these effects should be more pronounced for smaller firms. To examine this prediction we estimate equation (33) separately for the bottom 20% of firms in our sample in terms of size, defined as the log ratio of book assets to the industry mean. As we see in columns (3) and (4), the effect of firm and competitor innovation is concentrated in small firms. For firms in the lowest quintile, increasing firm innovation form the median to the 90-th percentile is associated with a reduction in the likelihood of exit by 0.8 to 0.9%. By contrast, the effect of the top 80% of the firms is substantially smaller by a factor of four. Similarly, the positive effect of innovation by competitors is concentrated in the smaller firms. The estimated marginal effects for the top 80% are actually negative, but not statistically different from zero.

III.E Firm productivity

The results of the previous section imply that innovation is followed by reallocation of resources towards innovating firms. For this process of reallocation to be efficient, innovation should be associated with higher factor productivity. Since output prices are not available at the firm level we focus on revenue-based measures of productivity. We use the estimates of firm total factor productivity (TFP) of Imrohoroglu and Tuzel (2013), who construct measures for Compustat firms using the Olley and Pakes (1996) procedure.

In our model, a firm's revenue-based total factor productivity TFPR equals

$$TFPR_{ft} = 1 + \left(\frac{\sum_{j' \in J_{ft}} \theta_{j' K_{jt}-1}}{\sum_{j' \in J_{ft}} \theta_{j' K_{jt}-1} \, \chi_{j' K_{jt}}^{1-\frac{1}{\alpha}}} \right) \phi_{ft}. \tag{34}$$

A firm's TFPR is a function of the average price markup in its product portfolio. The markup for the non-patent protected goods is equal to zero. Following a successful patent application, a firm's TFP (34) increases since it has acquired monopoly rights to a new product vintage; if that vintage also represents a larger quality improvement χ than the average in the firm's portfolio, firm TFPR further increases. Successful innovation by competing firms results in a higher probability of the firm losing its monopoly power and thus to a decrease in TFPR.

We take (34) to the data using a specification similar to (29)

$$g^{x}_{ft,t+\tau} = a(\tau)\, \xi_{ft} + b(\tau)\, \xi_{I \setminus ft} + \gamma_t + d_I + c\, Z_{ft} + u_{ft+\tau}. \tag{35}$$

Since the effect of innovative activity on firm revenue might be slow to realize, we examine horizons τ of one to seven years. We plot the estimated coefficients $a(\tau)$ and $b(\tau)$ in Panels (a) and (b) of Figure 4, respectively, along with 90 percent confidence intervals.

We find that innovation is associated with substantial changes in firm-level measures of productivity. An increase in firm innovation from the median to the 90-th percentile is associated with an increase of 2.1% to 2.3% in firm-level productivity over a period of 4 to 7 years. By contrast, a comparable increase in innovation by competing firms results in a decrease of 1.1% to 2% in firm-level productivity over the next 7 years. These numbers are economically meaningful, given that the median to 90-th range of log TFP in our sample is equal to 0.40.

Our results in this section contribute to the discussion on the determinants of productivity differences across firms. While some of these differences likely reflect imperfections in the measurement in productivity, a substantial fraction reflects real differences in firms' ability to generate revenues for given capital and labor inputs. Understanding why these differences exist – and persist over time – and relating them to specific aspects of firms' economic activity remains a significant challenge (see Syverson, 2011, for an excellent survey). Constructing a measure of innovation activity and relating it to firm TFP allows us to quantify the extent to which these productivity differences can be accounted by differences in product quality or improvements in the production process that are embodied in patents. In terms of the fraction of TFP dispersion explained, our results suggest that differences in innovation activity account for a comparable fraction of differences in TFP across firms as management practices (Bloom and Van Reenen, 2007). For this exercise, obtaining a more precise measure of innovative activity is important. For instance, performing the same exercise using citation-weighted patent counts results in point estimates whose economic significance is lower by a factor between 5 and 10, as we show in the online Appendix.

III.F Firm growth

So far, we find that innovation is associated with increases factor use and productivity increases for innovating firms. These findings suggest that own innovation should be followed by increased firm growth. However, innovation by competitors has the opposite effect. Hence, a natural question is to what extent innovation represents a zero-sum game, in which aggregate output remains unaffected and the only thing that changes is which firm gets to produce it. Since output prices are not available at the firm level, we focus on the model's predictions for firm revenue.

Total sales for firm f depend on its portfolio of patents for intermediate goods. As before, taking expectations over the possibility of the firm losing a patent to a competitor, its sales growth equals

$$g^S_{ft} \approx \frac{\theta_{jK_{jt}-1}}{\sum_{j' \in J_{ft-1}} \theta_{j'K_{jt-1}-1} + B_6} \Delta^+_{ft} - \lambda_{It}\, \phi_{ft-1} + \Delta \log Y_t - \Delta \log \hat{\theta}_t. \tag{36}$$

A firm's total sales increase as the firm acquires patents for new products, Δ^+ and these products are produced at a higher scale, θ_{jK-1}. Conversely, the firm's sales decrease when it loses a good to its competitors. These two effects are each increasing in the firm's own innovation, ξ_{ft}, and those of their competitors, $\xi_{I\setminus ft}$, respectively. The last term in equation (36) corresponds to changes in factor prices, which are absorbed by the time dummies in our specification.

We estimate the response of firm revenue S to the firm's own innovation ξ_f and innovation by its competitors $\xi_{I\setminus f}$

$$g^S_{ft,t+\tau} = a(\tau)\,\xi_{ft} + b(\tau)\,\xi_{I\setminus ft} + \gamma_t + d_I + c\,Z_{ft} + u_{ft+\tau}. \tag{37}$$

where $g^S_{ft,t+\tau}$ is growth in firm sales (including change in inventories) between time t and $t+\tau$. Our vector of controls Z includes log capital; log labor; two lags of firm sales; firm idiosyncratic volatility; industry and time fixed effects. We cluster the standard errors by firm.

As before, we focus on the estimates of a and b, which capture the effect of innovation of the firm and its competitors, respectively. Since the effect of innovative activity on firm revenue might be slow to realize, we examine horizons τ of one to seven years. We plot the estimated coefficients $a(\tau)$ and $b(\tau)$ in Panels (a) and (b) of Figure 4, along with 90 percent confidence intervals. We find that firm sales displays a positive and statistically significant response to an own-innovation shock ξ_f. A firm that experiences an innovation shock from the median to the 90th percentile experiences a 1.1% to 2.4% in firm sales over a period of 4 to 7 years. By contrast, an increase in competitor innovation from the median to the 90-th percentile is associated with a decline in firm sales by 1.8% to 2.2% over the same period.

To understand the net impact of innovation, we compute the increase in aggregate firm sales – within our sample of firms – that can be attributed to innovation. As before, we compute the aggregate change in firm sales, $\widehat{s}g_t = \sum_f \hat{g}^S_{ft,t+\tau} S_{ft} / \sum_f S_{ft}$ where $\hat{g}^S_{ft,t+\tau} \equiv \hat{a}(\tau)\,\xi_{ft} + \hat{b}(\tau)\,\xi_{I\setminus ft}$ is the component that can be attributed to innovation. Our estimates imply that the contribution of innovation to aggregate revenue growth is not trivial. At four years, we find that the next effect of innovation is close to zero at 0.03%. However, as we increase the horizon from five to seven years, we find that innovation accounts for an increase in total sales by 0.12% to 0.25%, in annualized terms., which corresponds to between 5 and 10% of the average GDP growth in the US over the last five decades.

IV Aggregate effects of innovation

Our analysis so far suggests that the net impact of innovation on the economy is substantial, leading to resource reallocation and growth. However, these findings should be interpreted with caution, since they are based on a sample of continuing firms. Since innovation is an important driver of firm exit, they likely are affected by survivorship bias. In this section, we revisit the question of the net impact of innovation by constructing aggregate and sectoral indices of innovation and relating the, to aggregate economic outcomes.

IV.A Constructing aggregate measures

Constructing an aggregate index of innovation activity can be challenging, since innovation has a heterogenous impact on firms. Hence, the exact way of aggregating stock market responses across innovating firms is not obvious. Our model provides some guidance. Specifically, aggregating over the stock market response of innovating firms – on the day the patent is granted – and scaling by their market capitalization

$$\frac{1}{P_t}\int_F \int_0^1 \Delta V^g_{jt}\,\Delta^+_{jft}\,dj\,df = B_5\,\lambda_t, \tag{38}$$

is proportional to the embodied shock λ. The constant B_5 depends on, among other things, the joint distribution of ν_{jk} and χ_{jk}. Accordingly, we construct industry- and economy-wide measures of innovation by aggregating our firm-level measure across the set J_t of firms across the entire economy, scaled by their market capitalization,

$$\hat{\lambda}_t = \sum_{f\in J_t} \Xi_{ft} \Big/ \sum_{f\in J_t} P_{ft}. \tag{39}$$

Industry-level analysis

We find substantial heterogeneity in the average level of innovation across industries. Using the definitions of the KLEMS dataset of Dale Jorgenson. the top 5 industries in terms of innovation activity, measured by their time-series average $\hat{\lambda}$ are Electrical and Non-Electrical

Machinery, Motor Vehicles, Instruments and Transportation Equipment. By contrast, the bottom 5 industries are Gas and Electric Utilities, Transportation, Printing and Publishing and Coal Mining. These differences in innovative activity is related to subsequent growth. In panel (a) of Figure 6, we plot the industry innovation measure $\hat{\lambda}_I$ 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 percent 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 percent over the second part of the sample.

Armed with a sectoral measure of innovation, λ_I, we revisit the question of the net impact of innovation on growth by estimating a specification similar to (37)

$$g^y_{It+k} = a_0 + a\,\lambda_{It} + \gamma_t + c\,Z_{It} + u_{It+k}, \tag{40}$$

where g^y_{It+k} is the growth rate in industry output k periods from now and λ_I is our measure of innovation at the industry. In analogy to the firm-level regressions, we include a vector of controls Z which includes: time effects; and two lags of the dependent variable y_{It}. We cluster the standard errors by industry. We again examine horizons of $k = 1$ to $k = 7$ years. We plot the estimated coefficients $a(k)$ in Panel (b) of Figure 6, along with 90 percent confidence intervals.

Our findings in this section are qualitatively similar with the results from aggregating the point estimates from our firm-level analysis. A one standard deviation shock to industry innovation is associated with a 8.7 percent in industry growth over a period of 7 years, confirming substantial net economic gains from innovation despite the rise in creative destruction.

Aggregate effects

Turning to the aggregate level, we find that a few large firms account for a significant fraction of 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.

We plot our aggregate innovation measure, $\hat{\lambda}$ in panel (a) of Figure 3. Our measure of innovative activity lines up well with the three major waves of technological innovation in the U.S. First, our measure suggests high values of technological innovation in the 1930s, consistent with the evidence compiled in Field (2003) and Alexopoulos and Cohen (2009) and Alexopoulos (2011). When we dissect our measure we find that firms that primarily contribute to technological developments during the thirties are in the automobiles (such as General Motors) and telecommunication (such as AT&T) sectors. This description is consistent with studies that have examined which sectors and firms led to technological developments and progress in the 1930s (Smiley, 1994). Second, our measure suggests higher innovative activity during 1960s and early 1970s – a period commonly recognized as a period of high innovation in the U.S (see 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 have brought about the latest wave of technological progress in the 1990s and 2000s, which coincides with the high values of our measure. In particular, it is argued that this is a period when innovations in telecommunications and computer networking spawned a vast computer hardware and software industry and revolutionized the way many industries operate. We find that firms that are main contributors to our measure belong to these sectors with firms such as Sun Microsystems, Oracle, EMC, Dell, Intel, IBM, AT&T, Cisco, Microsoft and Apple being the leaders of the pack.

For comparison, we also plot the number of patents per capital in panel (b), the aggregate investment rate in R&D from the BEA (c), and the number of technology books published from Alexopoulos (2011) in panel (d). Comparing these aggregate innovation series, we note three important points. First, our measure displays different behavior than the total number of patents, especially in the beginning and towards the end of the sample. The correlation between $\hat{\lambda}_t$ and the log number of patents is equal to 0.42 in levels and 0.11 in first differences. Second, our innovation measure captures 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 measure 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.

Since our aggregate innovation measure is denominated in dollar terms, it allows us to shed some light to the puzzle raised by Kortum (1993), among others, regarding the secular increase in the R&D to patent ratio. Indeed, as we see in panel (e), the ratio of R&D expenditures, deflated by the BEA R&D deflator to the total number of patents granted in the US exhibits a secular increase. Kortum (1993) examines three of the potential explanations using a structural model, namely i) a decline in the productivity in the research sector; ii) an increase in the value of patents due to market expansion; and iii) decrease in the patenting rate due to increased costs of patenting. Consistent with the conclusions in Kortum (1993), we find that the second explanation is likely. We construct the ratio of the mean value per patent – constructed as $\sum_{f \in J_t} \Xi_{ft}$ divided by total number of patents to firms in our sample – scaled by nominal R&D expenditures per patent. As we see in panel (f), this ratio of average benefit to average cost is mostly constant in the 1960's to late 1990's period, except for a spike at the end of the 1990's.

Last, when aggregating across firms in (39) we are only including the positive stock market responses of firms that innovate and omit any stock market declines by competing firms.

Hence, a potential source of concern is that we are overstating the aggregate technology shock. In our model, this is not a concern because the net benefit of innovation is positive, while both gains and losses are proportional to the aggregate embodied shock λ. However, in the data, the net impact of innovation need not be positive. One way to verify that our aggregation strategy (39) is sensible is by comparing the resulting technology series with the time series of the net effect of innovation on firm sales we constructed in Section III.F. The correlation between the aggregate series constructed in (39) to the net effect computed from our firm-level regressions is positive and ranges from 74% to 89% at horizons of 5 to 7 years.

IV.B Innovation and reallocation at the industry level

One limitation of our analysis using Compustat firms is that the aggregate effects we obtain apply only to publicly listed firms. To explore whether our inferences apply to the broader sample of all firms, we reexamine some of the model's predictions using industry-level data. We obtain measures of job reallocation and establishment turnover at the industry level from the US Census. The data is constructed using the methodology of Davis et al. (1998) and is available for the 1977 to 2010 period and covers nine industries, out of which we exclude financials and utilities. We estimate a specification as before,

$$j_{It} = a(\tau)\,\xi_{It} + \gamma_t + d_I + u_{ft}, \tag{41}$$

where j corresponds to measures of job reallocation. We present the results in Columns (1) to (7) in Table 8.

Our estimates suggest that innovation is associated with mostly job destruction rather than job creation. The economic magnitudes are substantial: increasing the level of industry innovation from the median to the 90-th percentile is associated with a 0.8% increase in the rate of job destruction – compared to the mean rate of 17.6%. Next, we decompose job creation and destruction to those due to continuing establishments, versus new entrants and exiting establishments. As before, we find no statistically significant effect on job creation, while the effects on job destruction are statistically significant only for the exiting establishments. The point estimate on job destruction by continuing establishments is economically similar to the effect of the total, however it is not statistically different from zero. Last, in column (7) we see a statistically and economically significant relation between the rate of job reallocation, defined as creation plus destruction minus the absolute value of net creation, and our innovation measure. Increasing the level of industry innovation from the median to the 90-th percentile is associated with a 1.2% increase in the rate of job reallocation – compared to the mean rate of 32.9%.

Indeed, establishment exit is an important component of the reallocative effects of innovation. In our model, the total measure of firms exiting the economy at time t is equal to

$$Exit_t = \sum_{n=1}^{\infty} |S^n_{t-1}| \, (\lambda_t)^n \left(1 - \frac{\overline{\nu}\lambda_t}{F}\right). \tag{42}$$

Equation (42) links the rate of creative destruction in our model to the rate of innovation λ. Under the assumption that the set of firms is sufficiently large, $\overline{\nu}\lambda_t/F < 1/2$, the aggregate rate of firm exit is increasing in the rate of embodied technological progress regardless of the distribution of product lines across firms. As we see in Column 8 of Table 8, industry innovation is accompanied by an economically significant increase in the rate of establishment exit. Increasing the level of industry innovation from the median to the 90-th percentile is associated with a 0.45% increase in the rate of job reallocation – compared to the mean rate of 11.3%.

Reconciling the findings in this section with the ones using Compustat firms, we note that the estimates in Section III.C are based on continuing firms, while here we take into account exiting establishments. We conclude that innovation is associated with substantial job reallocation,while once we take into account establishment exits, the effect on job creation is most likely negative.

IV.C Innovation and growth

In the last part of our analysis, we examine the extent to which our innovation measures account for short- and medium-run fluctuations in aggregate output growth and productivity.

In our model, the aggregate supply of labor is constant, hence output and productivity coincide. Growth is driven by the disembodied technology shock A and the rate λ at which the technology frontier expands,

$$g^y_t = \Delta \log A_t + (1-\alpha)\ln\left(\left(\chi - 1\right)\lambda_t + 1\right). \tag{43}$$

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.

We examine the relation between innovation and subsequent growth using three specifications. First, we estimate using a specification similar to (44)

$$g^y_{t+k} = a_0 + a\,\hat{\lambda}_t + c\,Z_t + u_{t+k}, \tag{44}$$

where Z contains two lags of the dependent variable. Second, 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. Third, we also compute responses using a vector-error-correction model (VECM), including a deterministic trend. The number of cointegrating relations are selected using the Johansen test, which suggests the presence of one cointegrating relation in all systems. The number of lags are selected using the Akaike-Information Criterion, which advocates a lag length of one to two years for each of the systems. Standard errors are computed by a bootstrap simulation of 500 samples. The impulse responses are computed by ordering the innovation shock λ last, so the technology shock affects the variables of interest only with a lag.

We plot the response of output and productivity to innovation in Figure 7, along with 90 percent confidence intervals. Our findings are broadly similar across specifications. We find that TFP increases by 1 to 2 percent over the first four years following a one-standard deviation increase, though the long-run effect is statistically different from zero only in our VAR/VECM specifications. The effect on output growth is similarly positive, but varies between 2.5% to 5% for a one-standard deviation increase in our innovation measure at the

8-year horizon. In our VAR/VECM specifications, the forecast error variance attributed to our innovation measure at the 8-year horizon ranges from 36 to 70 percent for TFP and 5 to 13 percent for output, depending on the specification.

Our findings in this section 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. We perform several robustness tests. For brevity, we summarize the results here and refer the reader to the Online Appendix for the full set of results. First, we include the cross-sectional average of idiosyncratic volatility $\overline{\sigma}$ to ensure that our innovation measure does not pick up movements in firm-level volatility. The shape and magnitudes of the impulse responses are similar in this specification. Second, 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. Our results are qualitatively similar in terms of statistical significance, but the economic magnitudes are somewhat smaller for TFP: productivity and output increase by 0.5 and 2.6% respectively at the peak following a one-standard deviation shock in our technological innovation measure. For comparison, the response of output to a one-standard deviation shock in $\log M$ is not statistically significant beyond the one-year horizon.

V Conclusion

We explore the role of technological innovation as a source of economic growth by constructing direct measures of innovation at the micro 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. Armed with a direct measure of innovation, allows us to test the predictions of a large class of models emphasizing creative destruction as a source of economic growth. Our empirical results confirm the models' predictions. We find that innovation is strongly associated with increases in output and productivity, as well as a rise in creative destruction.

References

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

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

Aghion, P. and P. Howitt (1997). *Endogenous Growth Theory.* The MIT Press.

Akcigit, U. and W. R. Kerr (2010). Growth through heterogeneous innovations. Technical report.

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

Alexopoulos, M. and J. Cohen (2009, May). Measuring our ignorance, one book at a time: New indicators of technological change, 1909-1949. *Journal of Monetary Economics 56*(4), 450–470.

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. Van Reenen (2010). Identifying technology spillovers and product market rivalry. Working paper, Stanford University.

Bloom, N. and J. Van Reenen (2007, November). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics 122*(4), 1351–1408.

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.

Cockburn, I. M., S. Kortum, and S. Stern (2002). Are all patent examiners equal? The impact of examiner characteristics. Technical report.

Comin, D. (2008). total factor productivity. In S. N. Durlauf and L. E. Blume (Eds.), *The New Palgrave Dictionary of Economics*. Basingstoke: Palgrave Macmillan.

Davis, S. J., J. C. Haltiwanger, and S. Schuh (1998, July). *Job Creation and Destruction*, Volume 1 of *MIT Press Books*. The MIT Press.

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

Fisher, J. D. M. (2006). The dynamic effects of neutral and investment-specific technology shocks. *Journal of Political Economy 114*(3), 413–451.

Gali, J. (1999, March). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review 89*(1), 249–271.

Giuri, P., M. Mariani, S. Brusoni, G. Crespi, D. Francoz, A. Gambardella, W. Garcia-Fontes, A. Geuna, R. Gonzales, D. Harhoff, and K. Hoisl (2007, October). Inventors and invention processes in europe: Results from the patval-eu survey. *Research Policy 36*(8), 1107–1127.

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.

Grossman, G. M. and E. Helpman (1991, January). Quality ladders in the theory of growth. *Review of Economic Studies 58*(1), 43–61.

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.

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.

Harhoff, D., F. M. Scherer, and K. Vopel (2003, September). Citations, family size, opposition and the value of patent rights. *Research Policy 32*(8), 1343–1363.

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.

Imrohoroglu, A. and S. Tuzel (2013). Firm level productivity, risk, and return. *Management Science*.

Justiniano, A., G. Primiceri, and A. Tambalotti (2011). Investment shocks and the relative price of investment. *Review of Economic Dynamics 14*(1), 101–121.

Justiniano, A., G. E. Primiceri, and A. Tambalotti (2010). Investment shocks and business cycles. *Journal of Monetary Economics 57*(2), 132–145.

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). 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). 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). 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 (2012). Compulsory licensing: Evidence from the trading with the enemy act. *The American Economic Review 102*(1), 396–427.

Moser, P., A. Voena, and F. Waldinger (2012). German-Jewish emigres and U.S. invention.

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

Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica 64*(6), 1263–97.

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

Romer, P. M. (1990, October). Endogenous technological change. *Journal of Political Economy 98*(5), S71–102.

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). 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.

Smets, F. and R. Wouters (2003, 09). An estimated dynamic stochastic general equilibrium model of the euro area. *Journal of the European Economic Association 1*(5), 1123–1175.

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

Syverson, C. (2004, May). Product substitutability and productivity dispersion. *The Review of Economics and Statistics 86*(2), 534–550.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature 49*(2), 326–65.

Tables

Table 1: Stock turnover around patent announcement days

Event	$l = -1$	$l = 0$	$l = 1$	$l = 2$	$l = 3$	$l = 4$
			I. Turnover			
A. Patent grant	-0.147	-0.008	0.0502	0.0588	0.0487	-0.074
	(-5.27)	(-0.68)	(3.63)	(3.22)	(1.78)	(-4.65)
B. Patent publication	0.152	0.255	-0.194	-0.385	0.114	-0.205
	(4.02)	(5.51)	(-3.03)	(-4.17)	(3.08)	(-3.07)
			II. Relative turnover			
A. Patent grant	-0.156	-0.006	0.055	0.061	0.047	-0.091
	(-6.74)	(-0.57)	(5.19)	(4.24)	(3.76)	(-6.71)
B. Patent publication	0.130	0.182	-0.015	-0.335	0.085	-0.191
	(4.33)	(7.25)	(-0.37)	(-8.41)	(2.73)	(-5.75)

Table shows the output of the regression of stock return turnover ($x_{t+l} = vol_t/shrout_t$) in Panel I and stock turnover relative to the market average ($vol/shrout - \overline{vol/shrout}$) in Panel II 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 2: Distributions of event returns (3-day) and innovation measure

Moment	N	C	r_f	$E[x_j \vert r_f]$	$\hat{\Theta}$ ($m, 1982)
Mean	12.6	10.2	0.15	0.46	7.9
Std. Dev.	18.8	20.1	5.41	0.28	23.0
Percentiles					
1%	1	0	-9.60	0.17	0.01
5%	1	0	-5.05	0.22	0.03
10%	1	0	-3.51	0.26	0.08
25%	2	1	-1.65	0.31	0.50
50%	6	5	0.07	0.39	2.20
75%	15	11	1.67	0.59	7.23
90%	33	24	3.92	0.73	17.07
95%	50	38	5.89	1.11	29.31
99%	88	90	12.05	1.71	89.47

Table reports the distribution at the patent level of the following variables: the number of patents granted to the same firm per day N; the number of citations C; the market-adjusted firm returns r_f on the 3-day window of patent grant dates; the filtered component of returns $E[x_j|r_f]$ related to innovation, using equation (16); and the filtered value of innovation $\hat{\Theta}_j$ using equation (15).

Table 3: Number of future citations and estimated value of patent

	Panel A. Grant Day			
	(1)	(2)	(3)	(4)
$\log \hat{\Theta}$	0.037	0.193	0.104	0.054
	(8.99)	(5.76)	(5.70)	(5.34)
R^2	0.289	0.296	0.401	0.426
	Panel B. Publication Day			
	(1)	(2)	(3)	(4)
$\log \hat{\Theta}$	0.030	0.047	0.036	0.014
	(5.74)	(5.75)	(4.39)	(1.26)
R^2	0.245	0.250	0.318	0.355
Controls				
Volatility	-	Y	Y	Y
Firm Size	-	Y	Y	Y
# patents granted same day	-	Y	Y	Y
Fixed Effects	T	T	TxC	TxC,F

Table shows the results from estimating equation (20) relating the log number of future citation N the patent receives to the filtered log dollar value of a patent, $\log \hat{\Theta}$. In panel A we show results constructed using the three day $(t, t+2)$ stock market reaction around the patent issuance date; in Panel B we show results using the three day $(t, t+2)$ stock market reaction around the day the application is publicized by the USPTO. We construct the filtered dollar value of innovation $\hat{\Theta}$ using equation (15), expressed in 1982 US dollars (billion). Depending on the specification we include grant- or publication-year T fixed effects; firm F fixed effects; USPTO 3-digit technology classification C interacted with year T fixed effects; firm idiosyncratic volatility; firm size, measured as market capitalization; and the number of patents granted in the same day. We cluster standard errors by announcement year and report t-statistics in parenthesis.

Table 4: Number of future citations and announcement day return, raw dollar reaction

	A. Raw measure							
	Grant Day				Publication Day			
N	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{\Theta}$	0.129	0.165	0.090	0.085	0.068	0.103	0.098	0.082
	(0.32)	(0.44)	(0.38)	(0.43)	(0.33)	(0.49)	(0.47)	(0.39)
R^2	0.092	0.103	0.221	0.265	0.101	0.108	0.185	0.233
Controls								
Volatility	-	Y	Y	Y	-	Y	Y	Y
Size	-	Y	Y	Y	-	Y	Y	Y
# patents granted same day	-	Y	Y	Y	-	Y	Y	Y
Fixed Effects	T	T	TxC	TxC,F	T	T	TxC	TxC,F

Table shows output of the regressions of number of future citations N on the raw five day $(t, t+4)$ stock market reaction around the patent grant day (columns 1-4) or the day the application is publicized by the USPTO (columns 5-8). We construct the filtered dollar value of innovation A using equation (15), expressed in 1982 US dollars (billion). We report log-log, semi-log and linear specifications. Depending on the specification we include grant- or publication-year T fixed effects; firm F fixed effects; USPTO 3-digit technology classification C interacted with year T fixed effects; firm idiosyncratic volatility; firm size, measured as market capitalization; and the number of patents granted in the same day. We cluster standard errors by announcement year and report t-statistics in parenthesis.

Table 5: Descriptive statistics on firm-level innovation variables

	Mean	Median	SD	p10	p25	p75	p90
# Patents (1000's)	0.008	0.000	0.031	0.000	0.000	0.002	0.013
# Cites (1000's)	0.086	0.000	0.441	0.000	0.000	0.008	0.108
ξ_f	0.023	0.000	0.076	0.000	0.000	0.010	0.063
$\xi_{I\setminus f}$	0.080	0.038	0.116	0.001	0 .007	0.119	0.193
Net Investment	0.174	0.088	0.448	-0.053	0.025	0.221	0.439
Net Hiring	0.088	0.023	0.354	-0.132	-0.052	0 .146	0.305
Total Factor Productivity, log	-0.637	-0.638	0.400	-1.066	-0.841	-0.429	-0.180
Profitability	0.056	0.092	0.211	-0.110	0.027	0.142	0.205
Firm id. volatility, log	-3.523	-3.544	0.554	-4.232	-3.928	-3.148	-2.788

The table presents descriptive statistics for new patents granted (raw and citation weighted), our firm-level innovation measures (A_f), innovation by competing firms (A_I), firm net investment (growth in PPE), net hiring rate (growth in employement), and profitability (operating income plus depreciation over book assets).

Table 6: Firm-level reallocation

	A. Capital				A. Labor			
Horizon ($\tau = 1$)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ξ_f	0.090	0.127	0.138	0.165	0.025	0.043	0.057	0.079
	(5.75)	(8.00)	(9.44)	(11.36)	(1.78)	(3.12)	(4.27)	(5.91)
$\xi_{I\setminus f}$	-0.171	-0.167	-0.164	-0.150	-0.120	-0.120	-0.121	-0.108
	(-10.27)	(-10.12)	(-10.67)	(-9.77)	(-7.65)	(-7.68)	(-7.98)	(-7.14)
R^2	0.047	0.055	0.080	0.084	0.039	0.044	0.050	0.054
Horizon ($\tau = 2$)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ξ_f	0.181	0.217	0.227	0.249	0.079	0.094	0.105	0.121
	(9.08)	(10.76)	(11.85)	(13.13)	(5.18)	(6.15)	(7.06)	(8.15)
$\xi_{I\setminus f}$	-0.241	-0.236	-0.232	-0.219	-0.106	-0.105	-0.105	-0.095
	(-12.33)	(-12.15)	(-12.62)	(-11.91)	(-6.20)	(-6.16)	(-6.33)	(-5.69)
R^2	0.071	0.077	0.095	0.098	0.060	0.064	0.068	0.071
Horizon ($\tau = 3$)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ξ_f	0.258	0.293	0.302	0.326	0.113	0.126	0.136	0.148
	(9.88)	(11.12)	(11.86)	(12.85)	(6.16)	(6.86)	(7.55)	(8.27)
$\xi_{I\setminus f}$	-0.305	-0.296	-0.293	-0.278	-0.109	-0.106	-0.107	-0.099
	(-12.62)	(-12.33)	(-12.69)	(-12.04)	(-5.23)	(-5.11)	(-5.24)	(-4.81)
R^2	0.086	0.091	0.106	0.108	0.073	0.076	0.080	0.081
Controls								
Fixed Effects	I,T	I,T	I,T	I,T	I,T	I,T	I,T	I,T
Size	Y	Y	Y	Y	Y	Y	Y	Y
Firm volatility	-	Y	Y	Y	-	Y	Y	Y
Lag Dep (1 lag)	-	-	Y	Y	-	-	Y	Y
Profitability	-	-	-	Y	-	-	-	Y

Table reports point estimates of equation (29), relating firm-level (ξ_f) and competitor ($\xi_{I\setminus f}$) innovation activity to capital (panel A) and labor choices (panel B). The firm-level measure of innovation ξ_f is defined (24); innovation by competing firms $\xi_{I\setminus f}$ refers to the average level of innovation of other firms in the same 3-digit SIC industry, defined in equation (26). Depending on the specification, we control for lagged values of firm size (log capital or number of employees); profitability; firm log idiosyncratic volatility; lagged values of the dependent variable; and industry (I) or time (T) fixed effects. Standard errors are clustered by firm. All variables are winsorized by year at the 1% level.

Table 7: Innovation and Likelihood of Firm Exit

	(1)	(2)	(3)	(4)
ξ_f	-0.0611	-0.1053		
	(-2.33)	(-2.92)		
ξ_f × SMALL			-0.1238	-0.1410
			(-2.31)	(-2.22)
ξ_f × LARGE			-0.0396	-0.0448
			(-1.90)	(-1.79)
$\xi_{I\setminus f}$	0.0013	0.0027		
	(2.43)	(3.19)		
$\xi_{I\setminus f}$ × SMALL			0.0017	0.0023
			(3.18)	(2.54)
$\xi_{I\setminus f}$ × LARGE			-0.0023	-0.0030
			(-1.62)	(-1.63)
Fixed Effects	-	T	-	T

The table reports the results from a logistic regression of firm exit – defined as firms which exit the database with CRSP delisting code 400-499 – on firm innovation ξ_f and innovation by competing firms $\xi_{I\setminus f}$. Our sample contains 209 such liquidation events in our sample, corresponding to 1.4% of the firms and 0.13% of the firm-year observations in our sample. We include time dummies in columns (1) and (2). We cluster by firm. We report marginal effects, evaluated at the median of each variable, and *t*-statistics in parenthesis using standard errors computed using the delta method.

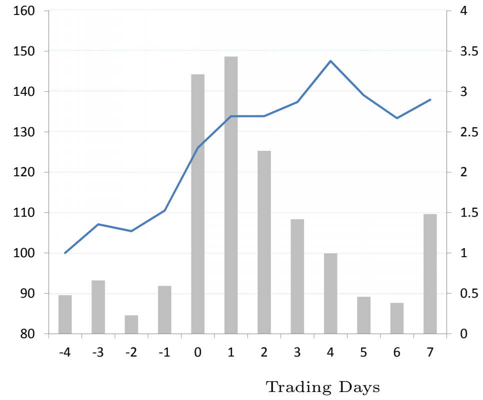
Table 8: Innovation and Industry Reallocation

	Job Flows							Establishment
	Creation			Destruction			Reallocation	Exit
	Total	Continuing Births		Total	Continuing	Deaths		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ξ_I	-2.725	-1.732	-0.971	6.883	4.231	2.612	10.530	3.861
	(-0.62)	(-0.64)	(-0.51)	(1.88)	(1.36)	(3.23)	(2.13)	(2.29)
R^2	0.831			0.766			0.853	0.732
Fixed Effects	I, T	I, T	I, T	I, T	I, T			

Table relates our industry-level innovation measure to job reallocation and establishment turnover. 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.

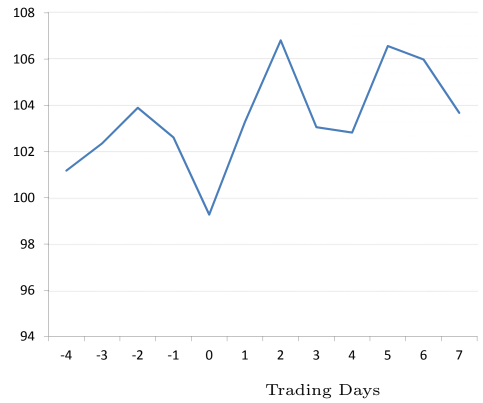
Figure 1: Some illustrative examples

(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. Volume data is not available for Canon. Note that Canon reported a 6% fall in pre-tax profits on Aug 19 (two days subsequent to the patent grant).

Figure 2: Relation between stock market reaction and number of citations across placebo experiments

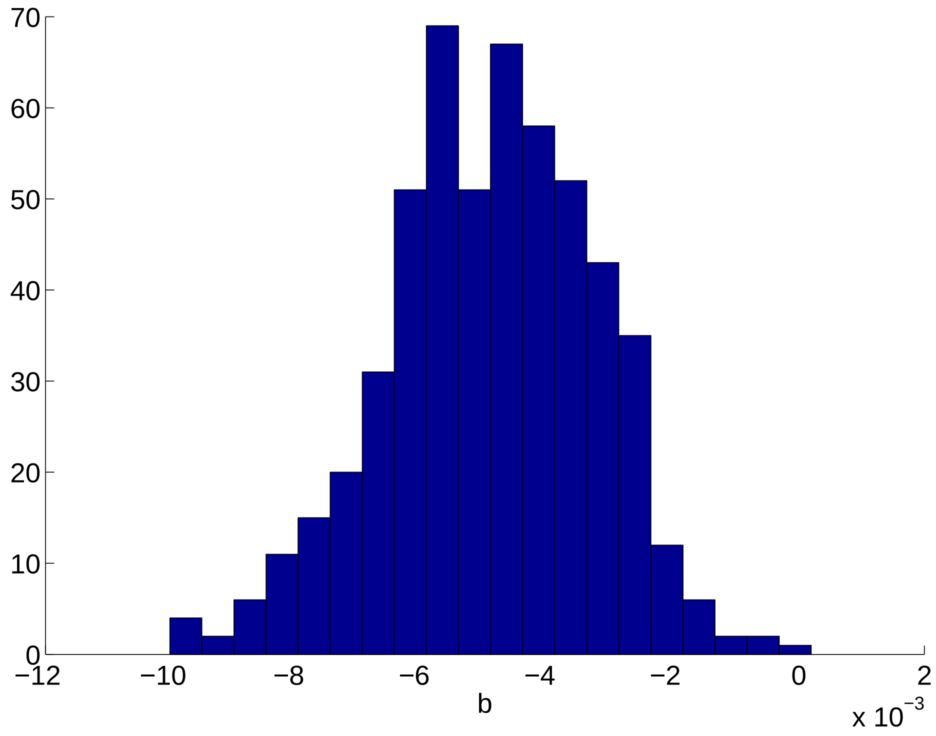
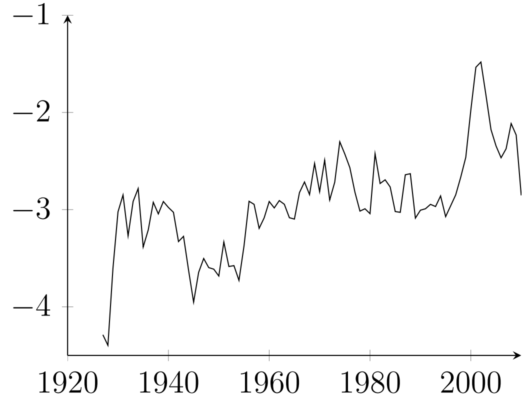
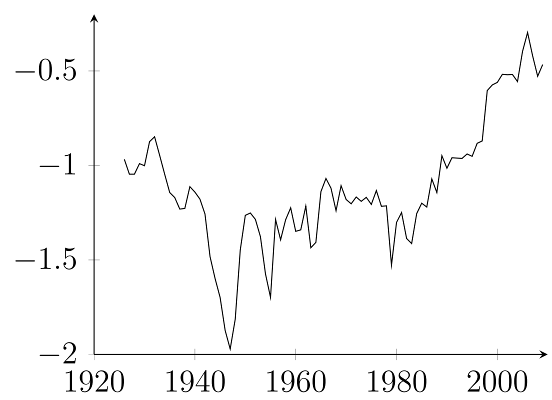


Figure plots distribution of estimated coefficients $\hat{b}$ across 500 placebo experiments, corresponding to the specification in column (4), row 1 of Table 3

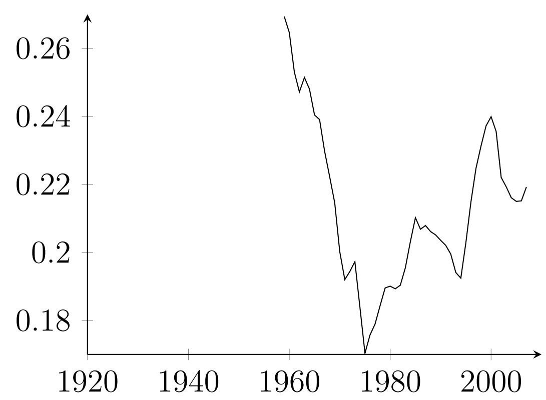
Figure 3: Aggregate measures of innovation



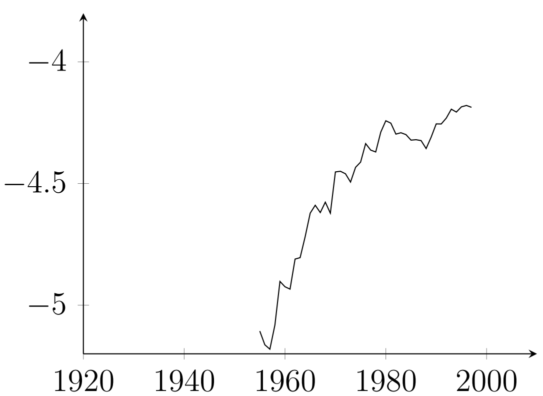
(a) Innovation measure, log



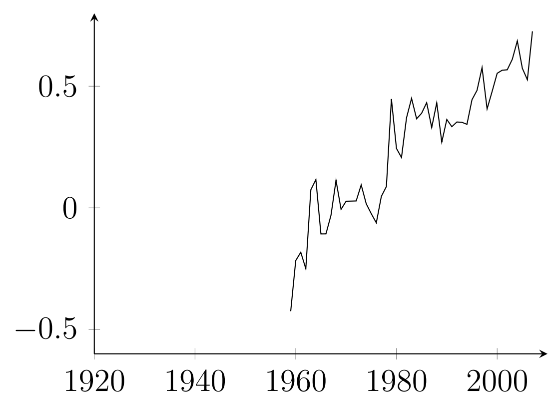
(b) Patents per capita, log



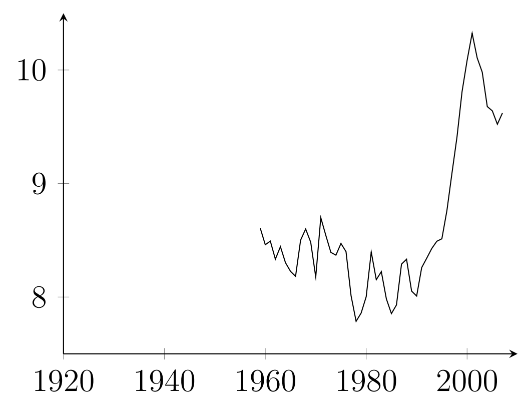
(c) R&D Investment, rate



(d) New technology books per capita, log

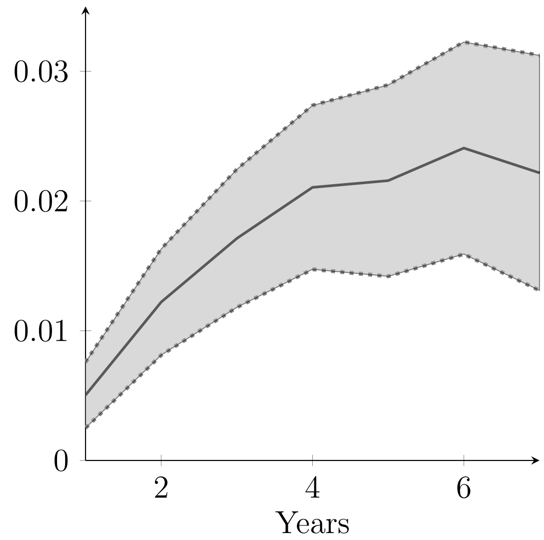


(e) R&D Expenditure / Patent, log

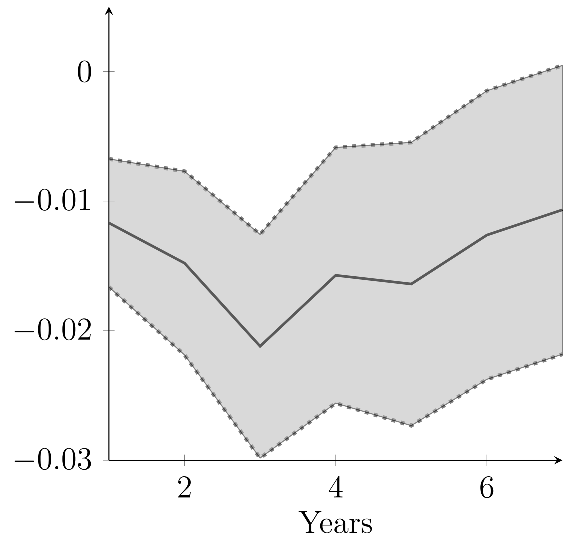


(f) Value/ patent to R&D Expenditure / Patent , log

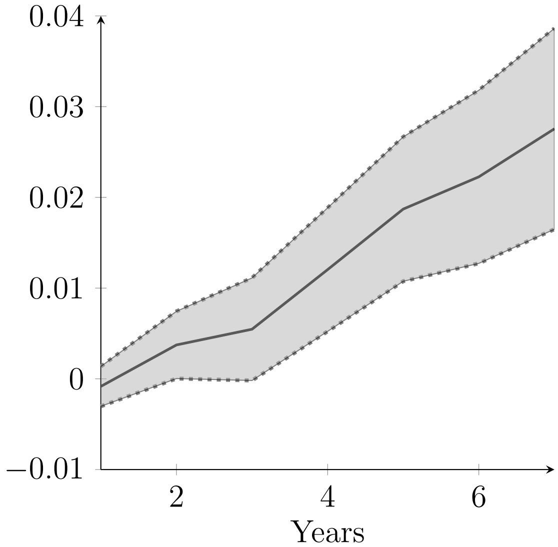
Figure 4: Innovation and firm output and productivity



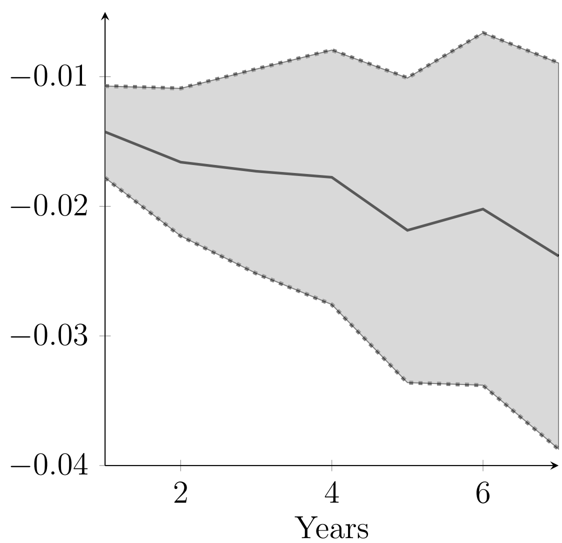
(a) Firm productivity and own innovation A_f



(b) Firm productivity and competitor innovation A_{If}



(c) Firm output and own innovation A_f



(d) Firm output and competitor innovation A_{If}

Panels (a) and (b) of Figure plot coefficients $a_1(k)$ and $a_2(k)$ (and 90% confidence intervals) of a regression of k-period ahead firm sales growth on innovation of firm (A_f) and competitors (A_I) using the specification (37) in main text. Panels (c) and (d) plot the corresponding responses for log firm total factor productivity. We control for lagged values of log capital and labor; two lags of the dependent variable; and industry (I) and time (T) fixed effects. We cluster the standard errors at the firm level.

Figure 5: Impact of innovation on aggregate sales

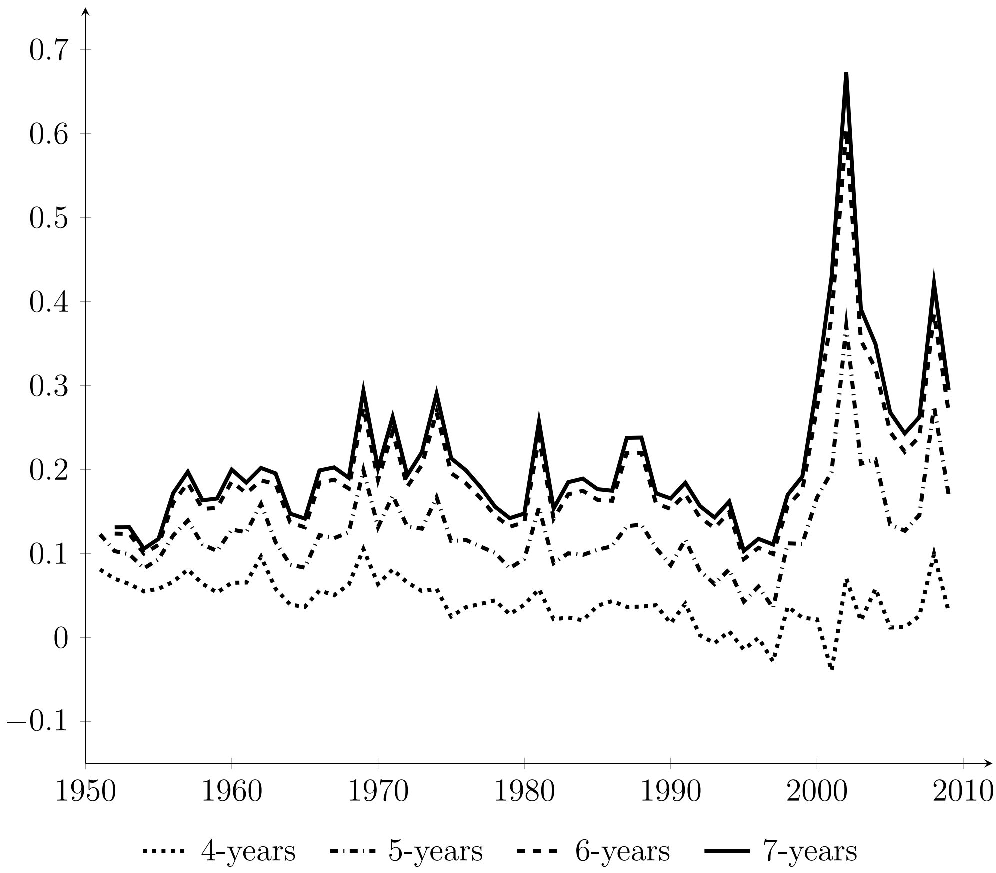
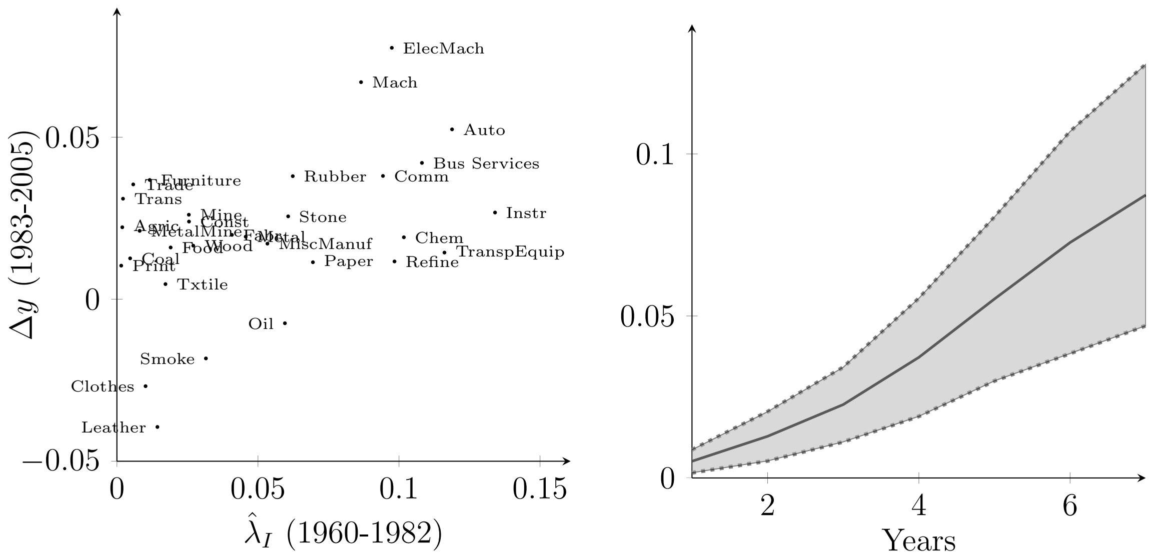


Figure 6: Innovation and Industry Growth



(a) Innovation and industry growth, long-run

(b) Innovation and industry growth, impulse response

Figure relates innovation to industry growth. Panel (a) plots the average output growth rate of 34 industries during the 1983-2006 period, versus the amount of innovation in 1960-1982. Panel (b) plots coefficients $a_1(k)$ (and 90% confidence intervals) of a regression of k-period ahead log firm output on innovation of industry (A_I) using the specification in equation 44. Controls include lagged values of log capital and labor; two lags of the dependent variable; and time (T) fixed effects. Standard errors are adjusted through the Newey-West procedure, with maximum lag length set equal to the number of overlapping observations plus two. Data is from Dale Jorgenson's 35-sector KLEM. Output is measured as value added in constant prices.

Figure 7: Innovation and aggregate output and productivity

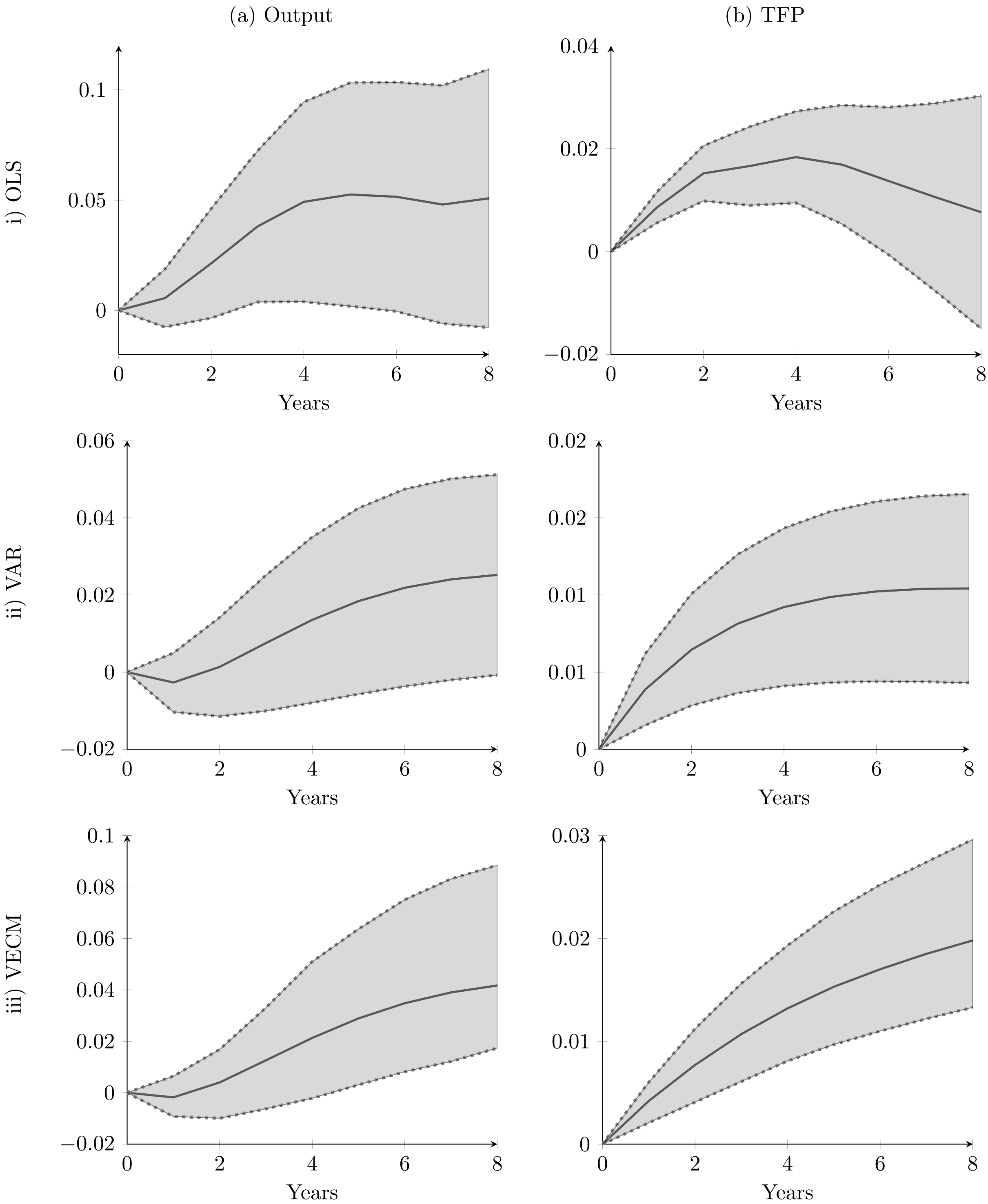


Figure shows impulse response of output and productivity to innovation using three specifications: i) OLS using equation (43); ii) bi-variate VARs; and iii) bi-variate VECM. In the last two cases, we obtain impulse responses by ordering our innovation measure last. We include a deterministic trend in the VECM. We select lag length based on the AIC criterion. Dotted lines represent 90% confidence intervals using standard errors are computed using 500 bootstrap simulations.