The Economic Effects of Scientific Shocks

Ruben Gaetani and Matteo Li Bergolis*

November 27, 2015

PRELIMINARY AND INCOMPLETE

Abstract

We combine data on scientific publications from the Web of Science, patent records from the USPTO and balance sheet information on publicly traded companies to measure firm-level response to the greatest scientific discoveries of our time. The publication of a groundbreaking paper is followed by a significant resource reallocation and output increase for responding firms. Measures of profitability are not affected on average, but this fact conceals large heterogeneity across different episodes. To explain these findings, we develop an endogenous growth model in which the returns to R&D investment are subject to information frictions. The model delivers a simple restriction that can be imposed on the data to separate breakthroughs from dead-end scientific discoveries. We test the model’s implications against our data: the empirical results support the idea that initial uncertainty systematically permeates the early stages of a new technology. Nevertheless, we provide suggestive evidence that discoveries that are unprofitable for responding firms can produce positive aggregate effects through dynamic technological spillovers.

*Gaetani: Northwestern University, Department of Economics. 2001 Sheridan Road, Evanston, IL, 60208 - gaetani@u.northwestern.edu. Li Bergolis: Cornerstone Research, 599 Lexington Ave, New York, NY, 10022 - mlibergolis@cornerstone.com. We thank for their comments Ufuk Akcigit, David Berger, Enrico Berkes, Lawrence Christiano, Matthias Doepke, Martin Eichenbaum, Benjamin Jones, Guido Lorenzoni, Kiminori Matsuyama, Lorenzo Michelozzi, Joel Mokyr, Alessandro Pavan, Giorgio Primiceri, and seminar participants at the 2014 Meeting of the North American Econometric Society in Minneapolis, Federal Reserve Bank of St. Louis and Northwestern Macro Lunch. Comments are welcome, errors are ours.
1 Introduction

Scientific discoveries are a precondition for most technological improvements. Mokyr (1990) argues that the importance of science in technological progress has expanded tremendously since the late 19th century. Advancements in basic science are increasingly recognized as an essential component of modern economic growth. An emerging body of literature is concerned with analyzing the market distortions that lead to a suboptimal provision of basic research. However, despite the widespread agreement on its central role in affecting long-run economic outcomes, scientific progress is mostly neglected by the literature on endogenous growth. In part, this is attributable to the assumption that basic and applied research respond to the same set of incentives and it is therefore innocuous to collapse them under a single operational idea. But a more practical reason is the lack of consistent measures of scientific progress, and a conceptual difficulty in linking it with observable economic variables.

This paper proposes a theoretical framework and a novel empirical approach to directly investigate the impact of groundbreaking scientific advancements on the real economy. Our empirical methodology relies on the observation that the greatest scientific discoveries of our times are by their own definition unexpected and, importantly, do not affect all firms in an industry to the same extent. For example, the publication of a revolutionary theory, the synthesization of new molecules and the discovery of new chemical reactions can open up unprecedented innovation possibilities for firms with compatible technological characteristics, while potentially leaving other competing firms indifferent. This paper analyses the role of these events (“scientific shocks”) as fundamental drivers of firm dynamics and aggregate productivity.

Using data on over 16 million academic publications from the Web of Science between 1980 and 2002, we isolate 182 very high impact research articles in various scientific fields. These articles represent the most cited pieces of original research published in their respective fields in a given year. The appearance of a seminal paper is interpreted as a shock to the information of firms about the evolution of their innovation possibilities. In order to identify responding firms, we use a string matching algorithm to single out patents in the USPTO universe that reference those papers. This procedure delivers 5,491 patents with a successful link, and a visual analysis suggests that the algorithm produces a very good match. For those patents originally assigned to a publicly traded company, the assignee can be matched with a firm identifier on Compustat, allowing us to establish an observable connection between seminal papers and innovating entities. For each firm in the final sample, we construct a measure of response to a seminal paper, defined as the number of
a firm’s patents that cite the paper in the twenty years following its publication divided by
the total number of patents that the firm produces over the same period. To the best of our
knowledge, this work is the first to create a direct link between academic papers and firms.

We use this novel index to assess the economic impact of scientific shocks at the firm
level. The appearance of a seminal paper is followed by a reallocation of physical capital,
labor and R&D resources towards responding firms. A one-standard deviation increase in
the measure of response to seminal papers induces an increase in the growth rate of capital
of 0.7% at a 2 years horizon, and of 1.2% at a 6 years horizon. Labor and total assets dis-
play similar trends. The response in the stock of R&D and R&D investment is even more
pronounced, reaching 1.6%-2% over a 6 years horizon. Output indicators are also positively
affected. Our regressions control for industry-year fixed effects, so that the resulting coeffi-
cients can be interpreted as measures of within-industry reallocation. The results are robust
to controlling for several firm-specific characteristics (size, stock of patents and profitability).

Surprisingly, measures of profitability and returns on capital are not significantly affected
on average by scientific shocks. This result can be rationalized in two possible ways. On
one extreme, information is perfect and factor markets are frictionless: a positive shock to
the innovation possibilities of a firm triggers a sufficiently strong resource reallocation that
equalizes ex-post returns across firms. This implies that scientific shocks do not affect the
rate of return on capital. Alternatively, information about a new scientific discovery and its
usefulness imperfectly transmits to investors, who react with skepticism to profitable dis-
coveries and with over-enthusiasm to unprofitable ones. The different informational biases
of scientific shocks deliver heterogeneous effects on the return on capital. On average, these
effects might compensate with each other and deliver a very small or even null estimated
average effect of scientific shocks on the rate of return of capital. In the second part of the
paper, we develop an endogenous growth model that we use to disentangle these two alter-
native explanations. This distinction turns out to be crucial to shed light on the transmission
mechanism of scientific shocks to the real economy.

We consider an environment where two competing sectors produce the same output
using different, although interdependent, technologies. Each sector is randomly hit by sci-
entific discoveries that affect how efficiently innovation effort (R&D) converts into new tech-
nologies. Innovation effort, in turn, is endogenously determined by agents’ optimal choices,
given their perception of the innovation possibilities. Science and R&D are intrinsically com-
plementary, since innovators cannot improve upon the current state of technology in the ab-
sence of a good scientific base. Agents choose how to allocate inputs and invest in applied
research to turn the insights of basic science into productive economic processes. However,
the fundamental value of new scientific insights is observed only with noise: this imperfect
observability captures the initial uncertainty on the technical applicability of a new discovery. Agents’ expectations about the potential of the scientific advancement determine the intensity of inputs and R&D effort deployed, while its fundamental value determines how effectively innovation effort translates into a higher level of technology.

The model delivers robust predictions on the economy’s response to fundamental and noise shocks. After a fundamental shock, resource reallocation is slow and persistent, reflecting both the progressive learning that follows the initial skepticism, and the gradual building of new technologies in response to the novel scientific insight. After a noise shock, resource reallocation has a boom-bust shape, with capital quickly reverting to the other sector as disillusion replaces the early wave of enthusiasm. However, the initial optimism temporarily pushes the innovation effort above its natural level, and dynamic technological spillovers imply that the long-run level of productivity is positively affected also in the case of noise shocks. Importantly, the model is able to separate the two shocks through a simple sign restriction: fundamental shocks are characterized by an increase in both investment and the rate of return on capital, while noise shocks induce a negative comovement of investment and the rate of return on capital. The intuition behind this result is that systematic noise in the information received by the agents leads to an under-reaction of capital in the former case and to an over-reaction in the latter case, compared to the response under perfect information (that would leave relative returns unaffected).

This sign restriction is imposed on the dataset that we build in the first part of the paper, in order to test directly the implications of the theory. As a first step, we apply the sign restriction to separate seminal papers in two bins: fundamental (or “breakthrough”) shocks, followed by a short-run increase in the rate of return on assets among exposed firms, and noise (or “dead-end”) shocks, that induce a short-run drop in the rate of return on assets. As a second step, we characterize the response of output and resource reallocation after the two types of shocks. Consistently with the predictions of the model, breakthrough shocks are followed by a slow and persistent reallocation of resources towards responding firms that reaches 1.6% per standard deviation over a 6-years horizon. Conversely, dead-end papers are followed by a reallocation of resources that is indistinguishable from the former on impact, but quickly vanishes to zero over a 4 to 6 years horizon.

We then provide suggestive evidence of breakthrough and dead-end scientific shocks borrowed from our dataset. We argue that scientific discoveries that turn out to be unprofitable for responding firms can indeed generate positive long-run effects by pushing up the intensity of resources employed in research. The history of technology is rich in examples of innovations that, although driven by misinterpreted or overemphasized scientific results, generated important spillovers and led to substantial technological improvements. This has
been true both for successful technological advancements generated by the application of erroneous scientific principles (such as Berthollet’s chlorine bleaching and hot-air balloon prototypes) and for unsuccessful technologies that ultimately produced important spillovers to other fields (such as Brunel’s atmospheric railway and Ericsson’s Novelty locomotive).

Overall, the empirical analysis suggests that scientific shocks are an important driver of firm-level dynamics and can help explain why some firms flourish and become technological leaders in their markets and other firms fail. The data also support the idea that systematic uncertainty permeates the early stages of new technological waves, with skepticism and over-enthusiasm emerging in turn as natural consequences.

Related Literature

This paper is related to three main strands of prior work. First, we contribute to the literature on the identification of technology shocks and the assessment of their effects on economic activity. The macroeconomic literature has mostly focused on the measurement of the current state of technology, for example, through the calculation of total factor productivity as a Solow residual, that is, the component of output that is unexplained by measurable inputs. As argued in Basu et al. (2006), this measurement is contaminated by several elements that are unrelated to technological progress, such as increasing returns and imperfect competition. Technology shocks have been considered for a long time as a “black box,” but in recent years, increasing attention has been devoted to understanding the nature of those shocks. Adams (1990) considers the role of expansion of scientific knowledge on productivity by introducing the stock of knowledge directly as an input in the firm’s production technology. He derives an industry-level time series of aggregate scientific knowledge based on the number of scientific articles published each year and finds that these measures predict productivity growth. We share with Adams (1990) the goal of understanding the role of scientific knowledge on technological progress, but we focus on seminal scientific contributions that originate new waves of innovation, and we conduct a disaggregated analysis that allows us to capture the heterogeneous effects of different kinds of scientific papers at the firm level. More recently, Alexopoulos (2011) constructed an aggregate, direct measure of technical change based on the number of book titles in the field of technology published each year, finding that this indicator predicts economic activity. Even if not plagued by the same limitations of Solow residuals, this measure is an indicator of the outcome of technological progress and is silent on the process through which improvements in basic science translate into more efficient technologies. As far as our empirical approach is concerned, our work is related to more recent studies that construct accurate measures of innovation at the firm and industry level. For example, Kogan et al. (2012) combine patent data at the
firm level with the stock market response to information about new patents to construct a measure of innovation that predicts output growth. Differently from this approach, we do not use patents directly as an index of innovation; rather, we use patents to construct a firm-level measure of exposure to academic research, and we focus on estimating the effects of scientific advancements on the exposed firms.

This work also contributes to the understanding of the impact of shifts in expectations on economic activity. Recent literature focuses on how expectational shocks - orthogonal to fundamentals - can generate cyclical, short-run fluctuations and explain part of the observed variation of output and consumption over the business cycle. Lorenzoni (2009) shows that positive shocks to expectations about future productivity generate effects that are comparable to demand shocks, namely, a short-run comovement between output and inflation. Barsky and Sims (2012) show that positive shocks to consumer confidence can be at least partially attributable to news about future productivity; they identify shocks to consumer confidence and estimate a positive long-run effects of the latter, raising some doubts about the non-fundamental interpretation of changes in expectations. Our paper contributes to the aforementioned literature by endogenizing productivity and by postulating that expectations can affect short-run and long-run outcomes directly through their impact on innovation.

From a theoretical point of view, our model is reminiscent of the literature on Directed Technological Change started by Acemoglu (2002). Differently from this literature, we allow for a richer innovation structure, endogenous inputs, and incomplete information. Our formulation defines an equilibrium that is stable around a balanced growth path while staying clear of corner solutions. The model can be written in linear form, which makes the agents’ signal extraction problem simple to define.

**Layout**

The remainder of the paper is organized as follows: Section 2 introduces the dataset and presents the preliminary analysis on the economic effects of scientific shocks. Section 3 describes the model, derives the theoretical predictions and discusses the identification strategy. Section 4 confronts the theoretical predictions with the data and provides suggestive evidence of the mechanism at work. Section 5 concludes.
2 Data and Preliminary Analysis

The first step of the empirical analysis entails linking shocks that occur in the scientific world with observable firm-level variables. To this end, we first need to identify major scientific discoveries, and then establish the identity of the firms that responded to them. We achieve this by combining three main sources of data.

First, in order to identify major scientific advancements, we use the Web of Science (WoS), the most comprehensive available database on academic publications. It assembles bibliographic information on articles published in peer-reviewed journals, conference proceedings and other academic platforms, and includes a total of more than 32 million articles published between 1945 and 2012. For each published item, we retrieve the publication year, the entire set of citations referenced by the item, the name of the first author and the journal (or other platform) on which the item was published. WoS adopts a classification system of scientific series based on three broad categories (Science, Social Sciences and Arts & Humanities) and several detailed disciplines.

Second, in order to link papers to firms, we use paper citations contained in the reference section of patents issued by the United States Patent and Trademark Office (USPTO). The USPTO releases the full text of all the patents issued since January 1976. We focus on patents issued until 2010, for which a reliable crosswalk to Compustat firms is available.¹ Every patent contains a dedicated section where any non-patent item (mostly academic papers) that is relevant for the development of the invention is properly referenced (patent references are listed in a separate section). Paper citations in patents are rare and meaningful events: there are almost 4 million patents issued between 1976 and 2010, the average patent citing only 2.94 non-patent items, for a total of about 11.5 million citations, a low number compared to the 16.6 million items in the universe of potential papers we consider.

Finally, firm-level information is obtained from the Compustat database accessible via WRDS. The database covers all publicly-traded firms in the United States from 1950 onwards. The advantage of this database is that it includes data on R&D expenditures and a system of identifiers that allows to easily map listed companies into patents’ assignees. To avoid truncation problems with the paper-patent matched data, we will focus on the years between 1984 and 2010. Our analysis will take into account only continuously innovative firms, defined as those entities that have filed at least one patent application in each of the 5-year moving windows over the considered period. Only two-digit industries with positive response to at least one paper are included in the sample. Missing values are interpolated assuming a constant growth rate across years. This gives a final sample of 29,910 firm/year

¹To link each patent to its firm’s identifier in Compustat, we use the database constructed by Kogan et al. (2014) that is publicly available on the author’s webpage.
observations, which cover 3,961 firms in 20 two-digit SIC industries. Figure 2.1 shows the distribution of remaining firms across industries in 1990 (left-panel) and 2000 (right-panel) respectively. The sample is heavily loaded on industries in the 35-38 range (industrial machinery, electronics and instruments), although in 2000 it is visible a shift towards codes in the 72-79 range (services).

### 2.1 Identifying the seminal papers

Every journal is assigned a main discipline and possibly one or more secondary fields. We focus on the primary discipline and discard journals that fall under Social Sciences and Humanities. We then aggregate the 172 remaining disciplines in 12 macro-subjects (details can be found in Appendix). To evaluate the scientific impact of each paper, we compute the number of citations received by the item in the nine years following the publication (i.e. for a paper published in 1995, we consider all citations received in the period 1995-2003). To avoid truncation problems, we focus on papers published between 1980 and 2002.

Each paper in the sample is classified as seminal if at least one of the following two conditions is met:

1. The paper received more citations in the nine years following its publication than any other paper in its own macro-subject.

2. The paper ranks among the top 10 papers based on citations received in the nine years following its publication, compared to papers published in the same year in all the macro-subjects.
Condition 1 requires a paper to be the highest-impact piece of research produced in its macro-subject in a given year. This requirement insures that we include groundbreaking papers in fields characterized by consistently lower citation counts. Condition 2 is imposed in order to capture groundbreaking research that would not satisfy Condition 1 due to competing papers in the same macro-subject that appeared in the same year. Note that, since a paper can satisfy Condition 1 and Condition 2 at the same time, the number of effective seminal papers can vary year by year.

We further clean the resulting list by excluding all the items for which it is possible to infer (from either the title or the abstract) that they do not represent original research papers (e.g. an article that simply establishes new terminology or new notation can easily turn out to be highly cited, but would not be relevant for our analysis). An additional filter requires the paper to be cited by at least one patent whose assignee can be linked to a firm identifier in Compustat. The final list includes 182 papers with a number of nine-year forward citations ranging from 186 to 19,385 and assigned patent citations ranging from 4 to 282. The average paper in the final list has received 2,743 citations in the nine years following its publication. Figure 2.2 shows a (winsorized) histogram of the density of resulting papers against the corresponding nine-year forward citations (left-panel) and the assigned patent citations (right-panel).

Figure 2.2: Distribution of citations of seminal papers from scientific papers 9 years after publication (left-panel) and from patents assigned to Compustat firms (right-panel). The distribution is winsorized at the 5% level for graphical clarity.

---

2The complete list of papers, inclusive of the bibliographic information, is available upon request.
2.2 Measuring firm-level response

We use an automatized algorithm to search for a match between each paper’s information (title, author and publication year) and non-patent items referenced in the full-text of each USPTO patent. As a result, each of the 182 seminal papers is matched to every USPTO patent that cites it. This procedure delivers 5,491 matches in patents whose assignee can be linked to a Compustat identifier (with an average of 30.17 patent citations per paper).\(^3\) This mapping allows us to construct an index of response of each company in the Compustat database to each seminal paper. In particular, the response of firm \(i\) to scientific shock \(p\) is constructed as:

\[
R_p^i = \frac{\text{Patents citing } p_{i, t_p, t_p+19}}{\text{All Patents}_{i, t_p, t_p+19}}
\]  

where \(t_p\) is the year in which the scientific shock is identified to occur. To account for the natural lag in the implementation of the scientific discovery, we set \(t_p\) as the year in which the first patent citing paper \(p\) is filed. \(R_p^i\) is the ratio of patents filed by the firm citing paper \(p\) over the total number of patents filed by the same firm, where the time horizon is a window of 20 years after the shock. We interpret this measure as capturing the technological characteristics that make a firm more or less likely to take advantage of the insight contained in paper \(p\). Note that we use patent information as a simple indicator of the degree to which a firm is affected by the appearance of the discovery, instead of using patents as a direct measure of the innovation outcome.

The response index has a simple interpretation. A value of \(R_p^i\) equal to one means that each single patent application filed by firm \(i\) in the 20 years horizon cites paper \(p\), while an exposure equal to zero means the firm \(i\)'s patenting activity has completely ignored paper \(p\). There are two reasons for which we use this ratio instead of the raw number of patents citing a given paper. First, it is comparable across firms of different size. Second, since our objective is to gauge the effect of scientific shocks on firms’ dynamics, it is important that our measure identifies changes in dependent variables (e.g., capital, labor and output) only through variation in the composition of patenting activity. In other words, if a firm doubles its capital and its patents without changing their composition in favor of paper \(p\), this specification, contrary to an unnormalized measure, will not attribute the change in capital to the change in the absolute number of patents citing \(p\).

Highly cited research is by its own definition unexpected: it is natural to assume that whoever is able to foresee the appearance of an insight with the potential of an astonishingly high scientific impact, would rather be the first to produce the paper containing the

\(^3\)The details on the algorithm are available upon request. Visual inspection confirms that the procedure produces a very good match.
insight itself. However, there are two main endogeneity concerns. First, it is possible that direct subsidies from companies to research institutions make the arrival of a seminal paper an endogenous event with respect to the dynamics and characteristics of responding firms. However, economic incentives themselves put a strict discipline on such a possibility. An economically valuable piece of research is unlikely to be published in a scientific journal before the beneficiary firm has fully exploited its economic potential through intense patenting activity. Second, it is possible that the ability of a firm to take advantage of novel groundbreaking research depends on unobservable characteristics that are correlated with the outcome variables of interest. To address this possibility, in ongoing work we perform an instrumental variable analysis where we predict a firm’s response to a discovery by looking at a firm’s propensity to cite prior related work in the period preceding the paper’s publication.\(^4\)

At each point in time, the overall response of a firm to papers appeared \(\tau\) years ago is defined as:

\[
R_{i,t}^\tau = \sum_{p \in P_{t-\tau+1}} R_i^p
\]  

\(^4\)First stage results suggest that this ex-ante information on firm’s patenting is highly informative of a firm’s propensity to respond.
Table 2.1: Marginal effects of a logit regression where the dependent variable is equal to one if the firm has positive response to at least one seminal paper appeared in the last 6 years. Industries are 2-digit SIC codes. Standard errors are clustered at the firm level.

<table>
<thead>
<tr>
<th></th>
<th>Positive response to papers appeared in the last 6 years</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Log average patents</td>
<td>0.0489***</td>
<td>0.0541***</td>
<td>0.0442***</td>
<td>0.0445***</td>
</tr>
<tr>
<td></td>
<td>(0.0020)</td>
<td>(0.0032)</td>
<td>(0.0036)</td>
<td>(0.0036)</td>
</tr>
<tr>
<td>Log Total Assets</td>
<td>-0.0050*</td>
<td>-0.0228***</td>
<td>-0.0209***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0026)</td>
<td>(0.0038)</td>
<td>(0.0040)</td>
<td></td>
</tr>
<tr>
<td>Log R&amp;D Expenditures</td>
<td>0.0343***</td>
<td>0.0335***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0055)</td>
<td>(0.0054)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.0017*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year and Industry f.e.</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N. Obs</td>
<td>29,901</td>
<td>29,901</td>
<td>28,172</td>
<td>28,172</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.41</td>
<td>0.41</td>
<td>0.44</td>
<td>0.44</td>
</tr>
</tbody>
</table>

for $\tau \geq 1$. This indicator can be loosely seen as the fraction of patents issued between $t - \tau + 1$ and $t - \tau + 20$ that cite any of the seminal papers whose shock is identified to occur in $t - \tau + 1$ (this set is denoted by $P_{t-\tau+1}$). However, note that by construction $R^\tau_{i,t}$ can be larger than one, as a single patent can cite more than one seminal paper.\(^5\)

Roughly 9% of the firm-year observations in the sample have positive response to any shock occurred within the past 6 years. Table 2.1 explores some correlations between the probability of responding to a seminal paper and some relevant firm characteristics. Not surprisingly, having a higher stock of patents increases the probability of responding. However, controlling for the number of patents, larger firms (companies with higher total assets) have a lower chance of reacting. Higher R&D intensity substantially improves a firm’s exposure to the scientific shocks, while age and probability of responding have a negative correlation.

The number of firm-year observations with positive response to a paper hitting in the same year (namely, observation for which $R^1_{i,t} > 0$) is 831, which implies that on average each of the 182 papers in the sample affects 4.56 companies. Figure 2.3 shows a histogram of $R^1_{i,t}$ conditional on $R^1_{i,t}$ being positive (the measure in the histogram is winsorized at the 0.5% level). The standard deviation of $R^1_{i,t}$ is 1.09% for the entire sample and 6.09% for the observations with a positive value.

\(^5\)In practice, this instance only occurs once in the dataset in one firm-year observation.
2.3 Empirical Specification

The assumption that we maintain in this paper is that original groundbreaking discoveries are qualitatively different from regular research, as they can open up tremendous innovation possibilities for firms with complementary characteristics. A firm learning about these possibilities can respond through costly investment in R&D and become more productive. This process will also attract resources and increase output, while the response of the return on capital and various measures of profitability will depend on the efficiency of capital markets in equalizing the marginal returns across firms. This hypothesis will be formalized in the model in Section 3, where we make explicit assumptions on the information structure of investors and innovators. In this section, we run some preliminary analysis to investigate this effect empirically.

Resource Reallocation and Output Response

The main empirical specification takes the following form:

\[ \Delta \% y_{i,s,t} = \alpha + \delta_{s,t} + \sum_{\tau=1}^{T} \beta_{\tau} R_{i,s,t}^{\tau} + \gamma X_{i,s,t} + \epsilon_{i,s,t} \]  

(2.3)

where \( \Delta \% y_{i,s,t} \) is the outcome variable (e.g. the growth rate of the capital stock) of firm \( i \) in two-digit SIC industry \( s \) at time \( t \), \( \delta_{s,t} \) is an industry-year fixed effect and \( X_{i,t} \) is a complete vector of controls. The coefficients \( \beta_{\tau} \) denote the marginal impact of an increase in the response measure on the dependent variable. Since the outcome variable is expressed in growth rates, for these specifications we consider the estimates of the cumulative impact, i.e. the \( \tau \)-periods ahead impulse response function:

\[ \tilde{\beta}_{\tau} = \sum_{r=1}^{\tau} \beta_{r}. \]

The set of controls includes a list of variables that can potentially bias the estimates of the \( \beta \)'s. First, we control for the stock of patents by including the lag of the logarithm of the 5-year moving average of patents filed by the firm. Note that since the sample only includes continuously innovative firms, this value is always well defined. To control for size, we include the lag of the book value of assets (or employment if total assets appear in the left-hand side). Finally, we control for profitability by including the lag of the rate of return on assets. In our baseline specification we consider a horizon of \( T = 6 \), but we show in the Appendix that nothing substantial changes if we consider shorter \( (T = 4) \) or longer \( (T = \)
SIGNIFICANT RESOURCE REALLOCATION AND OUTPUT INCREASE

Figure 2.4: Cumulative response of Physical Capital (PPEGT), total assets (AT), total employment (EMP) and value added (EMP*WAGE + OIBDP) in percentage change from their value at 0, following a one standard-deviation shock to the response measure. The figure shows point estimates and 90% error bands. Standard errors are clustered at the firm level. The regressions include (2-digit SIC) industry-time fixed effects, and control for the lagged value of total assets (or employment), the logarithm of the number of patents and firm’s profitability (ROA).

8) horizons instead. The growth rates are computed using the mid-point method,\(^6\) which basically imposes exit to be normalized to \(-2\), but we show in the Appendix that results are not qualitatively affected by removing exit from the analysis. Since the regression includes lags of several variables, entry (normalized to \(+2\) according to the mid-point method) is never explicitly considered in the baseline specification. In the Appendix we show that including entry observations in the analysis significantly increases the magnitude of the estimated coefficients. Standard errors are clustered at the firm level.

The top panel of Figure 2.4 shows the behavior of physical capital (left-panel) and total assets (right-panel) following a one standard deviation shock to the response index. Note that since the regression controls for industry-year fixed effect, the coefficients can be interpreted as indicative of resource reallocation within industries. The appearance of a seminal paper triggers a significant reallocation of physical capital towards responding firms, that reaches 1.2% per standard deviation over a 6-year horizon. This magnitude is large compared to a sample median of 7.4% and a sample average of 12.8%. The bottom panel of Figure 2.4 shows the corresponding impact on labor and output indicators, namely number

\(^6\)See e.g. Davis et al. (1998).
SIGNIFICANT INCREASE IN R&D INVESTMENT

Figure 2.5: Cumulative response of the stock of R&D and R&D expenditures in percentage change from their value at 0, following a one standard-deviation shock to the response measure. The figure shows point estimates and 90% error bands. Standard errors are clustered at the firm level. The regressions include (2-digit SIC) industry-time fixed effects, and control for the lagged value of total assets (or employment), the logarithm of the number of patents and firm’s profitability (ROA).

Figure 2.5 shows the response of R&D stock and R&D investment in response to a one-standard deviation shock in $R_{i,t}^{\tau}$. Both the R&D stock (left panel) and R&D investment (right-panel) responds positively and significantly. In the medium run, the magnitude of the response is quantitatively larger compared to the other inputs.

These findings are consistent with the fact that exposed firms receive an inflow of physical resources in response to news of an improvement in their innovation possibilities. Since our regressions control for industry-time fixed effects, this fact should be interpreted as reflecting reallocation of resources within, rather than across industries. In other words, firms in the same output market that respond differently to a scientific discovery experience different paths of capital and labor growth. The fact that R&D investment responds positively also suggests that exposed firms actively react to transform the scientific insights into useful technologies.

---

7 We compute value added as labor expenditures (the product of number of employees and average nominal wage) plus operating income before interests and depreciation (OIBDP).

8 The change in the R&D stock is computed using the perpetual inventory method with a depreciation rate of 10%. See Bloom et al. (2013).
NO RESPONSE IN PROFITABILITY AND RETURN ON CAPITAL

Figure 2.6: Response of Return on Assets (right-panel) and cumulative response of the output to capital ratio, in percentage change from their value at 0, following a one standard-deviation shock to the response measure. The figure shows point estimates and 90% error bands. Standard errors are clustered at the firm level. The regressions include (2-digit SIC) industry-time fixed effects, and control for the lagged value of or employment, the logarithm of the number of patents.

Profitability

We now verify if the same shock has a visible impact on the level of profitability enjoyed by responding firms. To this end, we estimate a regression similar to (2.3) with various measures of profitability as outcome variables:

\[
p_{i,s,t} = \alpha + \delta_{s,t} + \sum_{\tau=1}^{T} \beta_{\tau} R_{i,s,t}^{\tau} + \gamma X_{i,s,t} + \epsilon_{i,s,t} \tag{2.4}
\]

where \(p_{i,t}\) is either the rate of return on assets (ROA) or the growth rate in the ratio of output to physical capital. The variable ROA is obtained by dividing net income by total assets. The ratio of sales to physical capital is an indicator of returns on capital which has a direct counterpart in the model of Section 3.\(^9\) Both measures are winsorized at the 1% level. The equation controls for the lag of the dependent variable, as well as for the stock of patents and firm’s size, as in (2.3).\(^10\) Standard errors are again clustered at the firm level.

Figure 2.6 plots the coefficients \(\beta_{\tau}\) estimated in (2.4). Note that since in the ROA equation outcome variable is not in growth rates, the left-panel of Figure 2.6 plots the estimated coefficients directly instead of their cumulative value. There is no clear response in any of the two measures, neither in the short-run nor in the medium-run. Overall, profitability does not seem to be significantly affected by scientific shocks.

\(^9\)Output is computed as the sales (SALE) plus the change in inventories (INVT).

\(^10\)To control for firm’s size, we include in the regression the lagged value of the logarithm of employment.
There are two contrasting interpretations that are compatible with this finding. One extreme possibility is that information on the innovation opportunities offered by a scientific discovery is perfect. In this case, the scientific discovery will trigger a sufficiently strong reallocation of capital that equalizes the marginal return across firms. A contrasting possibility is that the ability of investors to foresee the economic potential of a scientific discovery is limited. In this case, agents’ expectations play a crucial role. If agents are too optimistic about the innovation possibilities that can stem from a new scientific contribution, a large amount of resources in the economy will be misdirected for the development of technologies related to that scientific insight and profitability will be lower than expected. On the other hand, if agents are overly skeptical, inputs and innovation effort will be initially too low and profitability will be higher than expected. The systematic presence of both episodes of over-enthusiasm and over-skepticism might generate an average response for profitability equal to zero, concealing heterogeneous episodes of positive and negative response.

In the next section, we develop an endogenous growth model to formally explore this possibility. Information frictions about the economic potential of new scientific discoveries generate successful and unsuccessful technological waves. The model delivers a simple sign restriction that can be applied to empirically identify the two, and a rich set of predictions that we verify directly against our data in Section 4. The final empirical analysis will give support to the model’s intuition, pointing to the fact that agent’s expectations may play a central role in the transmission process of science to the real economy.

3 Model

The theory that we present in this section rationalizes the choice between different technologies in an environment in which productivity is endogenous and there is imperfect information on the returns to innovative activity. The source of this uncertainty lies in the inability on the side of the agents to fully assess the potential of scientific discoveries that appear exogenously. The model can be seen as a basic version of Acemoglu’s (2002) model of Directed Technological Change. However, we impose a simple geometric structure that allows the equilibrium equations to be written in a narrow log-linear form without approximation. The linearity is essential to solve for the agents’ signal extraction problem that is at the heart of the mechanism we describe.
Setting

Consider an economy in which a single homogenous good is produced aggregating intermediate inputs produced by two separate sectors \( s = 1, 2 \) that adopt two different, although interdependent, technologies. The intermediate inputs are perfect substitutes, and the final good of the economy is simply the sum of the inputs produced in the two sectors:

\[
Y_t = Y_{1,t} + Y_{2,t}.
\]

Each intermediate input is produced according to the following production function:

\[
Y_{s,t} = K_{s,t}^\alpha \left( \int_0^{M_{s,t}} x_{i,s,t} \, di \right)^{1-\alpha}, \tag{3.1}
\]

where \( K_{s,t} \) is the physical capital that is employed in sector \( s \), \( M_{s,t} \) is the total number of varieties of machines available (in principle) in sector \( s \) at time \( t \), and \( x_{i,s,t} \) denotes the amount of machines of variety \((i,s)\) that are currently utilized in production. To simplify notation, let

\[
A_{s,t} = \int_0^{M_{s,t}} x_{i,s,t} \, di
\]

denote the total amount of machines employed in sector \( s \) at time \( t \). Later, we will refer to the variable \( A_{s,t} \) simply as the level of technology.

Capital owners

The economy is populated by a unit mass of risk-neutral capital owners, each of them endowed with \( \bar{K} > 0 \) units of capital that can be rented for one period to the representative firm of one of the two sectors for the competitive market price \( R_{s,t} \). Capital does not depreciate nor can new capital be built.\(^{11}\) However, capital is perfectly mobile across the two sectors, and capital allocation decisions taken in the past impose no constraints on capital owners’ current choice. As explained below, at the moment in which an allocation decision is taken, investors are unable to perfectly foresee the price at which capital will be rented, and therefore, they will have to form expectations about that. Up to degenerate equilibria (described below), investors will allocate resources in the two sectors so that in equilibrium,

\(^{11}\)To interpret this simplification, one can think of this setting as a partial equilibrium where total output is the output of a specific industry and the total amount of capital the economy devotes to the industry is fixed in the short-run, although it can be allocated to different types of technologies (sectors) within the same industry.
the return of capital is equalized in expectations:

\[ E^{k,1}_k [R_{1,t}] = E^{k,1}_k [R_{2,t}], \]

(3.2)

where the superscript \((k, 1)\) indicates that expectations are taken with respect to the information set of the capital owner \((k)\) and the first piece of information \((1)\) received by the investor has been incorporated. Without loss of generality, we can assume that capital owners are represented by a single investor that takes prices as given.

**Innovators**

Each sector is populated by a unit mass of innovators. Innovators use past knowledge to produce new ideas, which they embed into machines; they also produce and sell these machines as monopolists. Each innovator \(j\) in sector \(s\) exerts innovation effort \(\sigma_{j,s,t}\) to develop new ideas (machines) according to:

\[ M_{j,s,t} = \sigma_{j,s,t} e^{\eta_{s,t}} M^{1-b}_{s,t-1} M^b_{-s,t-1}, \]

(3.3)

where \(M_{s,t-1}\) and \(M_{-s,t-1}\) denote, respectively, the aggregate mass of machines available at time \(t-1\) in sector \(s\) and in the other sector (denoted by \(-s\)). The economy is hit stochastically by scientific discoveries that determine \(\eta_{s,t}\), an aggregate stochastic shock to the evolution of the innovation possibilities. The parameter \(b \in (0, 1)\) controls the extent to which the two sectors are technologically integrated. Since \(b > 0\), the sector with a relatively less advanced technology (lower variety of machines) will receive positive spillovers from the more advanced sector, while the sector with the better technology will receive negative spillovers from the less advanced one. This parameter can be interpreted as capturing complementarities in innovation across different industries. A large value of \(b\) implies that technology in the two sectors cannot diverge too much.

By exerting innovation effort \(\sigma_{j,s,t}\), the representative innovator incurs in a cost equal to:

\[ C_{j,s,t} = \frac{1}{\phi} M^{1-\alpha}_{s,t-1} \sigma^\phi_{j,s,t}, \]

(3.4)

where \(\phi > 1\). Note that, being the return to innovation linear and the cost of innovation convex, every innovator in sector \(s\) will choose the same level of effort \(\sigma_{j,s,t} \equiv \sigma_{s,t}^\phi\).

Equation (3.3) implies that old ideas cannot be directly used in current production but can only be used to facilitate the production of new ideas. This assumption preserves the geometric form of the law of motion for technology and allows us to compute the equi-
librium without resorting to approximations. Innovators will be granted monopoly power over newly-designed machines for one period, and they will be able to produce one and only one unit of each machine at zero marginal cost (namely, \( x_{i,s,t} \equiv 1 \)). Hence, the total amount of machines employed by sector \( s \) can be written as:

\[
A_{s,t} = \int_0^1 \int_0^{M_{i,s,t}} x_{i,s,t} \, di \, dj = M_{s,t},
\]

and the law of motion for \( A_{s,t} \) can be simply written as:

\[
A_{s,t} = \sigma_{s,t} e^{\eta_{s,t}} A_{s,t-1}^{1-b} A_{s,t-1}^b.
\]

Machines are rented to the intermediate good producer at their competitive price:\(^{12}\)

\[
w_{s,t} = (1 - \alpha) \left( \frac{K_{s,t}}{A_{s,t}} \right)^\alpha,
\]

so that innovator’s first order conditions dictate:

\[
\sigma_{s,t} = \left\{ (1 - \alpha) A_{s,t-1}^{a-b} A_{s,t-1}^b \right\}^{\frac{1}{\phi-1}}
\]

where the superscript \((\Sigma, 1)\) indicates that expectation is taken with respect to the information set of the innovators \((\Sigma)\) after receiving their pieces of information \((1)\). Again, as was the case with the representative investor, there is no loss of generality in assuming the existence of a single representative innovator in each of the two sectors, who takes the price of machines as given.

**Information and timing**

Keeping old ideas \( M_{s,t-1} \) fixed, technology at time \( t \) will be determined by an endogenous factor (innovation effort \( \sigma_{s,t} \)) and an exogenous shock (scientific discoveries \( \eta_{s,t} \)). When making their investment decisions, capital owners will try to forecast both components. They realize that high investment in a sector implies higher rental price of innovation (and hence higher innovation effort), but being price takers, they will neglect the impact of their choice on innovators’ best response.

The key to the strategic interaction between investors and innovators lies in the (first and second order) beliefs the two categories of agents hold about the evolution of the exogenous

\(^{12}\)Note that, although each innovator is a monopolist in its own machines, the machines are perfect substitutes for the intermediate good’s producer.
component $\eta_{s,t}$. In what follows, we explain how these beliefs are formed as a result of the information received exogenously and the equilibrium objects observed by the agents.

All agents enter each period with some prior distribution about the returns to innovation effort in sector $s$ in the previous period, $\eta_{s,t-1}$. Given the assumptions we will impose, the prior distribution for class of agents $I \in \{k, \Sigma\}$ will always be a normal random variable:

$$\eta_{s,t-1}^{I,2} \sim N \left( E \left[ \eta_{s,t-1} | T_{t-1}^I \right], V^{I,2} \right),$$

where the superscript 2 indicates that this prior distribution corresponds to the posterior distribution at the end of the last period, when all the information at the agent’s disposal has already been incorporated. Note that we drop the time subscript on the variance term, as we assume that the economy starts from a point in which the residual variance is constant and equal to the steady state Kalman filter variance.

For convenience, we divide each period in four sub-periods:

1. At the beginning of the period, a shock $\varepsilon_{s,t}^\eta \sim N \left( 0, \sigma_\eta^2 \right)$ realizes for each of the sectors without being observed directly by any of the agents. Fundamentals in sector $s$ are determined according to the following AR(1) process:

$$\eta_{s,t} = \rho \eta_{s,t-1} + \varepsilon_{s,t}^\eta.$$

2. In the second sub-period, a shock $\varepsilon_{s,t}^\nu \sim N \left( 0, \sigma_\nu^2 \right)$ realizes, and all the agents in the economy observe the following signal:

$$\nu_{s,t} = \eta_{s,t} + \varepsilon_{s,t}^\nu.$$

Based on the information representative investors have at their disposal, they allocate capital in the two sectors in such a way as to achieve:

$$E_{i}^{k,1} [R_{1,t}] = E_{i}^{k,1} [R_{2,t}].$$

The superscript $k, 1$ denotes that expectations are taken with respect to investors’ information set after the first signal $\nu_{s,t}$ is observed. The investor’s inability to predict the rental price of capital is grounded both in her imperfect information about the fundamentals $\eta_{s,t}$ and on the information innovators will receive, which will affect $R_{s,t}$ endogenously through innovation. Whether or not innovators observe directly the choice of the representative investor is irrelevant, since they are able to perfectly predict it by solving for the equilibrium allocation, given the signal they observe.
3. In the third sub-period, a shock $\epsilon_{s,t}^{\omega} \sim N(0, \sigma^2_\omega)$ realizes, and the representative innovator in sector $s$ observes a signal

$$\omega_{s,t} = \eta_{s,t} + \epsilon_{s,t}^{\omega}$$

and updates her expectations about $\eta_{s,t}$ accordingly (taking into account the signal $\nu_{s,t}$ observed in the previous sub-period as well). She chooses how much innovation effort to exert according to (3.7). This choice is not observed by the investor. The assumption we make about agents’ information is that innovators are strictly more informed about scientific possibilities than investors are.

4. Production and consumption take place. Prices are determined so as to clear markets. Investors observe the resulting rental price of capital in the two sectors, $R_{1,t}$ and $R_{2,t}$. Innovators observe the rental price of innovated machines, $w_{1,t}$ and $w_{2,t}$.

The information structure described above implies that, at the end of each period, innovators will be able to perfectly back out the state of fundamentals $\eta_{s,t}$, and they will enter period $t + 1$ without any residual uncertainty. This property results from the fact that they observe both their own research effort and, by looking at the market price of innovation, they can perfectly back out the state of fundamentals. On the contrary, upon observation of the rental price of capital, investors will only observe a combination of the fundamental shock and the noise shock received by innovators. This will be reflected in the signal extraction problem we describe below.

**Innovator’s signal extraction problem**

Innovators are assumed to be able to observe both $\nu_{s,t}$ and $\omega_{s,t}$. Their signal extraction problem does not depend directly on any endogenous object. Since they have no residual uncertainty about last period fundamentals (i.e., $V_{\Sigma,2} = 0$), their problem is trivial. Upon observation of the signals $\nu_{s,t}$ and $\omega_{s,t}$, their posterior distribution on $\eta_{s,t}$ will be

$$\eta_{s,t}^{\Sigma,1} \sim N \left( E_{s,t}^{\Sigma,1}, V_{\Sigma,1} \right),$$

where $E_{s,t}^{\Sigma,1} = E [\eta_{s,t} | \eta_{s,t-1}, \nu_{s,t}, \omega_{s,t}]$ is the expected value of $\eta_{s,t}$ and $V_{\Sigma,1} = Var [\eta_{s,t} | \nu_{s,t}, \omega_{s,t}]$ the residual variance. Applying the properties of conditional normal distributions,

$$E_{s,t}^{\Sigma,1} = \rho \eta_{s,t-1} + \Theta_\nu [\nu_{s,t} - \rho \eta_{s,t-1}] + \Theta_\omega [\omega_{s,t} - \rho \eta_{s,t-1}]$$
where \( \Theta_v = \frac{\sigma^2_\eta^2}{\sigma^2_\eta^2 + \sigma^2_\omega^2 + \sigma^2_\nu^2}, \) \( \Theta_\omega = \frac{\sigma^2_\omega^2}{\sigma^2_\eta^2 + \sigma^2_\omega^2 + \sigma^2_\nu^2}, \) and

\[
V^{\Sigma,1} = \frac{\sigma^2_\eta^2 \sigma^2_\omega^2}{\sigma^2_\eta^2 + \sigma^2_\omega^2 + \sigma^2_\nu^2}.
\]

Here, the superscript \((\Sigma,1)\) specifies that this posterior distribution is computed after the innovator has received her information (i.e., signals \( \nu_{s,t} \) and \( \omega_{s,t} \)) but before the fourth sub-period (when prices are observed).

**Investor’s signal extraction problem**

Now, consider the signal extraction problem of the investor that enters the period with a prior distribution over \( \eta_{s,t-1} \) with mean \( E_{k,2}^{s,t-1} \) and residual uncertainty \( V^{k,2} \) about last period’s fundamentals. Upon observation of the first signal \( \nu_{s,t} \), the investor updates beliefs as follows:

\[
\eta^{k,1}_{s,t} \sim N \left( E \left[ \eta_{s,t} | \eta^{k,2}_{s,t-1}, \nu_{s,t} \right], V^{k,1} \right),
\]

where:

\[
E \left[ \eta_{s,t} | \eta^{k,2}_{s,t-1}, \nu_{s,t} \right] = \rho E_{s,t-1}^{k,2} + \frac{\rho^2 V^{k,2} + \sigma^2_\eta}{\rho^2 V^{k,2} + \sigma^2_\eta + \sigma^2_V} \left[ \nu_{s,t} - \rho E_{s,t-1}^{k,2} \right]
\]

and

\[
V^{k,1} = \frac{\left[ \rho^2 V^{k,2} + \sigma^2_\eta \right] \sigma^2_V}{\rho^2 V^{k,2} + \sigma^2_\eta + \sigma^2_V}.
\]

At the end of the period, innovators and investors will observe their respective prices and update their beliefs again. As noted above, by observing her own effort and the outcome of such effort, the innovator will be able to perfectly back out \( \eta_{s,t} \), that is:

\[
E^{\Sigma,2}_{s,t} = \eta_{s,t} \quad V^{\Sigma,2} = 0,
\]

while the investor will only observe \( R_{s,t} \), which, conditional on \( \nu_{s,t} \), is a combination of \( \eta_{s,t} \) and \( \omega_{s,t} \), derived from the equilibrium condition. The solution to this problem requires solving the steady state Kalman filter and is described in the Appendix.

**Equilibrium**

We can solve for the equilibrium backward, starting from the choice of the innovators and then solving for the investor’s decision.
Equation (3.7) displays the level of innovation effort given the capital choice and innovators’ expectations about the fundamentals. Substituting for $A_{s,t}$ we get:

$$\sigma_{s,t} = \left\{ (1 - \alpha) K^a_{s,t} \left( \frac{A_{s,t-1}}{A_{s,t-1}} \right)^{b(1-\alpha)} E_t \left[ e^{(1-\alpha)\eta_{s,t}} \right] \right\}^{\frac{1}{\phi-1+\alpha}}. \quad (3.8)$$

The representative investor will attempt to predict the innovation effort that will be exerted and will combine this expectation with her posterior belief $\eta_{k,1}$. She will then allocate capital in the two sectors in such a way as to equalize the expected rate of return of capital in the two sectors. As shown in the Appendix, capital is allocated in the two sectors so as to satisfy the following condition:

$$\left[ \frac{K_{1,t}}{1 - K_{1,t}} \right] = \left\{ \left( \frac{A_{2,t-1}}{A_{1,t-1}} \right)^{\frac{2h(1-\alpha)}{\phi-1+\alpha} - (1-\alpha)} \frac{E_t^{k,1} [\xi_{1,t}]}{E_t^{k,1} [\xi_{2,t}]} e^{\left[ \frac{(1-\alpha)\Sigma}{\phi-1+\alpha} \right] [v_{1,t} - v_{2,t}]} \right\}^{\frac{\phi-1+\alpha}{(1-\alpha)(\phi-1)}}, \quad (3.9)$$

where:

$$\frac{E_t^{k,1} [\xi_{1,t}]}{E_t^{k,1} [\xi_{2,t}]} = \exp \left\{ \frac{(1 - \alpha) \rho \left[ 1 - \lambda \Sigma - \lambda \omega \right]}{\phi - 1 + \alpha} \left[ E_{1,t}^{k,1} - E_{2,t}^{k,1} \right] + \left[ \frac{(1 - \alpha) \lambda \omega}{\phi - 1 + \alpha} + 1 \right] \left[ E_{1,t}^{k,1} - E_{2,t}^{k,1} \right] \right\}. \quad (3.9)$$

From (3.9), it is straightforward to see the following:\footnote{Degenerate equilibria are “apocalyptic”, in the sense that they lead to the “end of the world” within two periods. To see this, consider a period in which $K_{1,t} = 0$ (the case of $K_{2,t} = 0$ is identical). Then, since $w_{1,t} = 0$, innovators will individually choose to direct innovation only to sector 2, that is, $\sigma_{1,t} = 0$ and $A_{1,t} = 0$. However, given the functional form of (3.6), $A_{2,t+1} = 0$ regardless of the choice of $\sigma_{2,t+1}$. From there, $A_{s,t+\tau} = 0$ for any $\tau \geq 1$.}

**Proposition 3.1.** There exists a unique equilibrium in which $K_{1,t} \in (0, 1)$. There exist degenerate equilibria in which $K_{1,t} = 0$ or $K_{1,t} = 1$.

The equilibrium will deliver the rental price of capital in each sector, $R_{s,t}$, as a function of exogenous disturbances only. Observing the rental price is equivalent to observing an additional noisy signal, $\tilde{r}_{s,t}$, that can be used by the investor to update her beliefs to $\eta_{k,2} \sim N \left( E_{s,t}^{k,2}, V^{k,2} \right)$. The filtering problem is described in the Appendix.

**Balanced growth path**

We focus on the symmetric balanced growth path (BGP) of the economy, and provide conditions below for its uniqueness and stability. In a BGP, the economy is not perturbed, all non-stationary variables grow at the same rate and all ratios stay constant.
In a symmetric BGP, \( K_1,t = K_2,t = \bar{K} \). Both \( A_1,t \) and \( A_2,t \) grow at gross rate

\[
\sigma^* = \left\{ (1 - \alpha) \left( \frac{\bar{K}}{2} \right)^\alpha e^{(1-\alpha)^2 V \Sigma_1} \right\}^{\frac{1}{1-\alpha}},
\]

while output and the rate of return on capital grow at gross rate \((\sigma^*)^{1-\alpha}\). We denote the net growth rate of technology by \( g_A^* = \sigma^* - 1 \) and generate a fictitious variable that imposes stationarity to the system. Namely, we recursively define the following:

\[
Z_0 = 1 \quad Z_{t+1} = (1 + g_A^*) Z_t, \quad t \geq 1.
\]

Then, non-stationary variables are normalized as follows:

\[
\begin{align*}
    r_{s,t} &= \frac{R_{s,t}}{Z_{s,t}^{1-\alpha}}, \\
y_{s,t} &= \frac{Y_{s,t}}{Z_{s,t}^{1-\alpha}}, \\
a_{s,t} &= \frac{A_{s,t}}{Z_{s,t}}.
\end{align*}
\]

The following proposition gives necessary and sufficient conditions for the symmetric balanced growth path to be globally stable. The proof is relegated to the Appendix.

**Proposition 3.2.** If \( \frac{a+2(\phi-1)}{2\phi} > b > \frac{a}{2\phi} \), there is a unique, non-degenerate balanced growth path. It is symmetric and globally stable.

**Dynamics**

For the purpose of the empirical analysis we perform in the next section, we are interested in the response of the economy to fundamental (or “breakthrough”) scientific shocks \((\epsilon_{1,t})\) and noise (or “dead-end”) scientific shocks that originate among investors \((\epsilon_{1,t})\). The main prediction of the model, which will serve as our identifying restriction, is that under reasonable parameter values, the relative return on capital, \( \frac{R_{1,t}}{R_{2,t}} \), responds positively to a fundamental shock and negatively to a noise shock. The following proposition, the proof of which is relegated to the Appendix, summarizes this result.

**Proposition 3.3.** Assume the economy is in balanced growth path at time \( t = 0 \). If \( \epsilon_{1,t}^\eta > 0 \), we have \( R_{1,t} < R_{2,t} \). If \( \epsilon_{1,t}^\nu > 0 \), we have \( R_{1,t} > R_{2,t} \), provided that \( \sigma_\nu^2 \) is sufficiently large, given \( \sigma_\eta^2 \) and \( \sigma_\omega^2 \).

To understand how the model allows us to separate the two shocks, it is useful to first consider an economy with perfect information about the evolution of \( A_{s,t} \). In such a world,
the rental rate of capital should be equalized across the two sectors in each period. Then, consider what happens when the evolution of $A_{s,t}$ is not perfectly predictable. After a fundamental shock, part of the information the agents receive will be attributed to the noise component. This will induce investors to under-respond to the observed piece of information, even after innovators’ optimal choice is taken into account. This initial skepticism on the economic and technical validity of a new scientific insight drives up the difference in the rental rate of capital on impact, and the presence of persistent informational frictions keeps this difference away from zero for many periods.

On the contrary, after a noise shock, investors erroneously believe that productivity in the high-expectations sector will be higher and optimally respond by reallocating capital toward that sector. Although innovation effort will be higher, the fact that fundamentals are unchanged implies that the resulting level of technology $A_{s,t}$ will not increase enough to compensate for the sharp increase in capital input, and this will produce a drop in the relative rental rate of capital on impact. Again, the presence of persistent information frictions implies that the convergence of the rental rates in the two sectors will take place over many periods.

Figure 3.1: Response of the relative rental rate of capital $\log \left( \frac{r_{1,t}}{r_{2,t}} \right)$ after a breakthrough shock $\varepsilon_{1,t}^{N} > 0$ (top panel) of one standard deviation and a dead-end shock $\varepsilon_{1,t}^{E} > 0$ (bottom panel). Solid line represents the equilibrium in which investors observe resulting prices at the end of each period. Dotted line represents the equilibrium in which realized prices are left unobserved.
Figure 3.2: Response of rate of capital in Sector 1 after a breakthrough shock \( \varepsilon_{1,t}^\eta > 0 \) of one standard deviation and a dead-end shock \( \varepsilon_{1,t}^\nu > 0 \), in percentage deviation from BGP.

Figure 3.1 summarizes this discussion.\(^\text{14}\) We show the dynamics of the relative rental rate of capital \( \log \left( \frac{r_1}{r_2} \right) \) after a breakthrough and a dead-end shock. We consider two cases: in the first, investors observe the market clearing prices at the end of the period (solid line); in the second, investors are not allowed to observe realized prices (dotted line). We set both shocks equal to one standard deviation of the fundamental component, \( \sigma_{\eta}^2 \). As expected, convergence towards the balanced growth value of zero is slower when prices are unobserved.

Now, consider the response of resource reallocation. Figure 3.2, shows the response of capital in Sector 1, as percent deviation from its BGP level, after a breakthrough shock and after a dead-end shock realized at time 2. On impact, the response of capital is identical under the two shocks: after having observed a positive signal, investors respond by allocating more capital to Sector 1, and in both cases they cannot distinguish whether the positive signal is due to fundamentals or noise, or a combination of the two. However, in the following periods, agents gradually learn the true nature of the shock: capital continues to flow in Sector 1 in response to a breakthrough shock, whereas it reverts back to Sector 2 in the case of a dead-end shock. Hence, the response of capital after a dead-end shock displays a boom-bust behavior, while instead a breakthrough shock induces a boom-boom response. It must be noted that, also after a breakthrough shock, capital eventually rebalances across the two sectors due to the technological spillovers that favor Sector 2.

\(^\text{14}\)To perform this qualitative exercise, we set parameter values such that the conditions in Propositions 2 and 3 are satisfied. The parameters are set as follows: \( \alpha = 0.3, b = 0.1, \phi = 1.8, \) and \( \rho = 0.5. \) The variances of the shocks are set to \( \sigma_{\eta}^2 = 0.1, \sigma_{\nu}^2 = 0.05, \sigma_{\omega}^2 = 0.1. \)
Finally, Figure 3.3 shows the response of normalized technology in the two sectors after a breakthrough and a dead-end shock. In the first case, technology in the two sectors diverges on impact: after observing a positive signal, capital and innovation effort increase in Sector 1, and returns to innovation are higher due to the positive breakthrough shock. Normalized technology in Sector 2 instead goes down, due to a reduced innovation effort and to the outflow of capital. Over time, agents learn the nature of the shock and innovation effort continues to increase, driving up technology in Sector 1. Eventually, following an initial overshooting, technology in Sector 1 converges to the new BGP, where technology is higher compared to its value in the previous BGP. Technology in Sector 2, conversely, converges in a slow catch-up to the same BGP, after the initial decrease.

In the case of a dead-end shock, we also have that technology in the two sectors diverges on impact, but this is only due to an increase in innovation effort in Sector 1: after observing a positive signal, innovation effort increases in Sector 1 and decreases in Sector 2. However, due to the absence of improvements in the returns to innovation, technology does not increase as much as in the case of a breakthrough shock. Innovation effort decreases in Sector 1 as the agents adjust their expectations, and at the same time, Sector 2 benefits from positive spillovers from the improved technology in Sector 1. Also in this case, the two sectors eventually converge to a new BGP where technology is higher than in the previous BGP. Hence, both after a breakthrough and after a dead-end shock, productivity is strictly higher in both sectors in the new BGP.

To sum up, the model delivers the following predictions about the endogenous response of variables to breakthrough and dead-end shocks:

1. After a breakthrough shock, we have a short-run increase in the relative rate of return on capital for the sector hit by the positive shock and a slow-moving reallocation of capital towards this sector. In the long-run, normalized technology increases in both sectors, overshooting the old BGP level.

2. After a dead-end shock, the relative rate of return on capital goes down for the sector hit by the shock, while capital is initially reallocated to the sector, and then it flows back. In the long-run, normalized technology increases in both sectors also in this case.

In the next section, we impose the restriction in Figure 3.1 directly on our data to test the model’s prediction directly.
4 Scientific Shocks: Short-run and Long-run effects

We proceed in two steps. First, we use the sign restriction derived from the model to separate breakthrough from dead-end shocks. Once the seminal papers in the sample have been assigned to those two bins, we separately investigate their effects on firm-level variables. This will allow us to confront the model’s predictions directly on our dataset. As we will show, the empirical results will match the model predictions and give support to the idea that imperfect ability to assess the economic value of a scientific discovery is a relevant component of the transmission mechanism of science to the real economy. One of the predictions of the model is that noise shocks can have positive long-run effects by driving up innovation effort in the short-run. At the end of this section, we discuss some suggestive evidence from our sample of seminal papers that supports this prediction.

To clarify, our classification of seminal papers in breakthrough and dead-end shocks is
not concerned with the scientific value of the discovery. Rather, it is intended to capture the economic profitability of the applications that can stem from such a discovery. Brilliant scientific insights can result in unprofitable applications for a variety of reasons, including unpredicted technical breaches, lack of demand, market price of inputs and complementary or substitute products, or even new regulations, on which we do not take a stand in the current work.

4.1 First step: identifying breakthrough and dead-end scientific shocks

Proposition 3.3 provides a simple restriction that can be used to separate fundamental from noise shocks, by looking at the response of the rate of return on capital of exposed firms relative to non-exposed ones. To impose this restriction on the collected shock, we run 182 regressions (one for each paper in the sample) of the following form:

\[
ROA_{i,s,t} = \alpha + \delta_{s,t} + \beta^p R_{i,s}^p \mathbb{I}_{\{t \in [\bar{t}_p, \bar{t}_p + 5]\}} + \gamma X_{i,s,t} + \epsilon_{i,s,t} \tag{4.1}
\]

where the coefficient of \( R_{i,s}^p \) has a superscript \( p \) to denote the fact that we estimate one coefficient for each paper. The dependent variable \( ROA_{i,s,t} \) denotes the return on assets of firm \( i \) in industry \( s \) at time \( t \). Every regression includes all firms belonging to industries with at least one firm with positive response index to paper \( p \) (that is, \( R_{i,s}^p > 0 \)). For example, if the industry “Transportation Equipment” has at least one firm with \( R_{i,s}^p > 0 \), all firms belonging to the industry “Transportation Equipment” are used to estimate (4.1). As in (2.4), the regressions control for the lag of the logarithm of the stock of patents and the lag of the logarithm of total employment.

In the model’s notation, we can interpret the appearance of the paper as a shock \( \nu_{s,t} > 0 \) to the innovation possibilities of responding firms (sector \( s \)). Non-responding firms in the same industry represent the opposite sector \((-s)\). The sign of the estimated coefficient \( \beta^p \) in (4.1) allows us to distinguish between the case of a fundamental shock \( (\epsilon^p_{s,t} > 0) \) or a noise shock \( (\epsilon^p_{s,t} > 0) \).

The sign of the coefficient \( \beta^p \) tells us whether firms responding to shock \( p \) have experienced higher or lower profitability than their industry-specific average in the six years following the shock \( (t \in [\bar{t}, \bar{t} + 5]) \). If, for a given paper \( p \), (4.1) yields a positive coefficient, it means that shock \( p \) induced an increase in the rate of return on capital for firms that have responded more intensely, relative to other firms in the same industry. This response mirrors the effect of a breakthrough shock in the theoretical model, therefore we classify all papers with estimated \( \beta^p \) as “breakthrough” papers. On the other hand, if \( \beta^p < 0 \), firms responding to \( p \) experience a decrease in the rate of return on capital relative to other firms in the
same sector: this case is equivalent to the effect of a dead-end shock in the model, hence we classify all papers with estimated $\beta^p < 0$ as “dead-end”.

Figure 4.1 plots a histogram of the estimated coefficients across the 182 regressions in (4.1) expressed in standard deviations of the independent variable. The procedure classifies a surprisingly high fraction of shocks as noise: 110 papers in the sample result as breakthroughs and 72 as dead-ends. The median estimated coefficient is equal to 0.32% for breakthroughs and $-0.31\%$ for dead-ends. These coefficients are large compared to a median ROA of 4.2% in the final sample of firms. However, the median coefficient over all the 182 regressions is equal to 0.11% (with a standard deviation of 2.3%) which confirms the lack of a clear average response in profitability following a scientific shock.

4.2 Second step: estimating the effects of scientific shocks

After having classified the papers into the two broad categories, we want to estimate the effects at the firm level of breakthrough and dead-end shocks, defined as the overall exposure of firms to breakthrough and dead-end papers as identified in the previous section. To this end, we compute a measure of overall exposure to breakthrough and dead-end papers
BREAKTHROUGH VS DEAD-END SHOCKS: RESOURCE REALLOCATION

Figure 4.2: Cumulative response of the stock of Physical Capital (PPEGT) in percentage change from their value at 0, following a one standard-deviation shock to the response measure of $R_{i,t}^{B}$ (blue line) and $R_{i,t}^{D}$ (red line). The regressions include (2-digit SIC) industry-time fixed effects, and control for the lagged value of total assets, the lagged value of profitability and of the logarithm of the number of patents.

appeared $\tau$ periods ago as:

$$
R_{i,t}^{B} = \sum_{p \in B_{t-\tau+1}} R_{i}^{p}
$$

$$
R_{i,t}^{D} = \sum_{p \in D_{t-\tau+1}} R_{i}^{p}
$$

(4.2)

where $B_{t}$ ($D_{t}$) is the set of breakthrough (dead-end) papers appeared in year $t$. These response indices are constructed in a way that is similar to (2.2), with the only difference that they only include the response of firm $i$ to fundamental ($R_{i,t}^{B}$) or noise shocks ($R_{i,t}^{D}$).

We then use these separate indices to assess the impact of the two types of shock on resource reallocation, output and profitability. To this end, we estimate equations analogous to (2.3):

$$
\Delta \% y_{i,s,t} = \alpha + \delta_{s,t} + \sum_{\tau=1}^{T} \beta_{\tau}^{B} R_{i,s,t}^{B} + \sum_{\tau=1}^{T} \beta_{\tau}^{D} R_{i,s,t}^{D} + \gamma X_{i,s,t} + \epsilon_{i,s,t}.
$$

As in (2.3), the estimation controls for the lag of the logarithm of total assets, the lag of the average stock of patents and the lag of the profitability measure (ROA). Note that we also include industry-time fixed effects, so that the estimated coefficients can be interpreted again as a measure of within-industry reallocation. As in Section 2, we define the cumulative
coefficients, \( \tilde{\beta}_B \) and \( \tilde{\beta}_D \), as:

\[
\tilde{\beta}_B = \sum_{r=1}^{\tau} \beta^B_r \quad \tilde{\beta}_D = \sum_{r=1}^{\tau} \beta^D_r.
\]

The figures in this section plot the cumulative coefficients after converting the response indices in units of its standard deviations.

The empirical results are strongly in line with the model’s predictions. Figure 4.2 plots the estimated coefficients for physical capital after a standard deviation breakthrough (blue line) and dead-end (red line) shocks. The dynamic response closely mirrors the one suggested by the model, in particular Figure 3.2. Following a breakthrough shock, reallocation is slow and persistent and reaches 1.6% of additional cumulative growth over a 6 years horizon. Following a dead-end shock, on impact, resources flow towards responding firms, but quickly revert back towards zero at a 4-6 years horizon.

Figure 4.3 reproduces the same exercise for employment, value added, R&D investment and the rate of return on assets. The findings are qualitatively consistent with the patterns described above. The response of the rate of return on assets is positive on average for breakthrough shocks and negative for dead-end shock, resembling the dynamics of Figure 3.1, as expected.

These patterns give support to the idea that initial uncertainty permeates the early stages of the development of a new technology. In some cases, optimistic beliefs can be proven wrong and resources follow a boom-bust path, as disillusion replaces the initial wave of enthusiasm. Investors, anticipating this possibility, react to profitable discoveries with skepticism, generating the slow and persistent reallocation observed in the case of breakthrough shocks.\textsuperscript{15}

One prediction of the model is that the initial jump in research activity that complements unprofitable discoveries can indeed result in long-run positive effects. In the remainder of this section, we discuss suggestive evidence from our sample of papers that give support to this intuition.

4.3 Long-run effects: Suggestive evidence

The list of seminal papers that we identify is rich in episodes that led to both successful and unsuccessful waves of technological innovation, that are recognizable by looking at the available anecdotal evidence. Unsurprisingly, many papers in the sample are concerned

\textsuperscript{15} In ongoing work, we use direct data on investors’ expectations to verify that the initial jump in investment is associated with high expectations on future profitability of responding firms.
BREAKTHROUGH AND DEAD-END SHOCKS: RESOURCE REALLOCATION AND RATE OF RETURN ON ASSETS

Figure 4.3: All the panels except for the last row show the cumulative response of, respectively, employment, value added and R&D investment in percentage change from their value at 0, following a one standard-deviation shock to the response measure. The figures in the last row show the response of the Return on Assets (ROA). The left column shows the response after a Breakthrough shock, the right column after a Dead-End shock. The figure displays point estimates and 90% error bands. Standard errors are clustered at the firm level. The regressions include (2-digit SIC) industry-time fixed effects, and control for the lagged value of total assets (or employment for the last row), the lagged value of profitability (except the last row) and of the logarithm of the number of patents.
with life science (mostly biology and medicine). Those are the fields that have undergone the strongest growth in scientific publications in the last decades. Journals of physics and chemistry are also widely represented, and are of specific interest, for example, for the synthetization of new materials or the development of new techniques in information and communication technologies.

In the early 1990’s, a widely cited article on human telomerase activity was published. Our matching algorithm recognizes intense patenting activity in response to this paper, mostly concentrated in a few publicly traded biotech companies that specialize in the commercialization of products for cancer. These companies have produced more than 15 patents citing the original paper (with the first patent being filed two years after publication) and enjoyed high profitability in the years following the appearance of the paper compared to similar firms in the same industry (the coefficient in the first step regression is +0.21%). Again in the field of life sciences, a paper published in the late 1990’s was followed by intense patenting activity from pharmaceutical companies that enjoyed high levels of profitability in the following years (the coefficient of the first step regression is +1.06%). Similarly, a paper published in the middle of the 1990’s on the treatment of alterations of apoptosis (programmed cell death) was the object of intense research activity from identified companies producing apoptosis related products, that enjoyed high returns in the years following the publication (the coefficient of the first step regression is +0.91%).

These are clear examples of pieces of scientific research that directly and successfully translated into profitable applications for responding firms. But this is not always the case. A high-impact article published in the early 1990’s developed a method of efficiently synthetizing a type of fullerene in considerable amounts. According to public sources, this method considerably boosted fullerene research. Our data suggests intense patenting activity in response to this seminal paper. No application of this fullerene could be commercialized in the short term. Firms responding to this seminal paper experienced low profitability compared to similar firms in the industry (the coefficient of the first step regression is −0.47%). Nonetheless, innovations developed during the initial period turned out to be crucial for future developments. Current applications span from medical uses to solar cell and hydrogen storage in fuel cell powered cars. A late 1990’s paper in our list developed a new polymerization technique and was followed by widespread scientific and applied research, mostly in the chemistry industry. However, responding firms experienced technical difficulties in initial applications. Profitability of responding companies was low compared to industry averages in the short term (the coefficient of the first step regression is −0.65%). Commercial applications of this technique are today widespread and, according to public sources, cover nearly all the molecules for which such technique is applicable.
5 Conclusion

In this paper, we interpret the exogenous advent of innovation possibilities as the appearance of groundbreaking scientific discoveries, and we investigate their impact on the real economy. We use the Web of Science to construct a new dataset consisting of seminal academic papers in science-related fields, and interpret their publication as exogenous shocks to innovation possibilities, i.e. “scientific shocks.” We then use patent information to link each paper to the firms that have exploited said scientific discovery. This allows us to establish an observable connection between the scientific world and firm level variables. We find that the appearance of a seminal paper is associated with a significant increase in physical capital, labor, R&D stock and investment and value added. However, indicators of profitability are not affected on average.

To explain these findings, we develop a two-sector environment with endogenous technological change, where the returns to innovation in one of the two sectors are subject to expectational shocks. The proposed model delivers a set of important predictions: (i) breakthrough shocks to innovation possibilities generate a positive comovement between investment and rate of return on capital, while dead-end shocks generate a positive response of investment and a negative response of the rate of return on capital in the sector hit by the shock; (ii) breakthrough shocks induce a slow-moving reallocation of resources towards the sector hit by the shock, while dead-end shocks produce a boom-bust response of inputs. We then apply these model predictions to conduct our empirical analysis. We classify scientific papers as breakthrough whenever they are followed by a positive response of the rate of return on capital; we classify them as dead-end whenever they are followed by a negative response of the latter. We quantitatively assess the dynamic response of capital, labor, R&D and output, and ROE of firms exposed to both breakthrough and dead-end shocks. The results are in line with the predictions of the theoretical model. Breakthrough shocks are characterized by a prolonged, slow-moving reallocation of resources towards the firms hit by the shock and by a persistently high level of value added. Dead-end shocks generate boom-bust reallocation of inputs, and a positive response of value added on impact, and a decline of these variables in the long-run.

We finally attempt to shed light on whether noisy flows of innovation can contribute to economic growth through dynamic technological spillovers. While the empirical estimation of these effects is still ongoing work, in this paper we have provided some suggestive evidence on the presence of spillover effects also from dead-end shocks.

Overall, the results in this paper suggest that scientific shocks are associated with significant movements in firm-level variables and can help explain why some firms flourish and
become technological leaders and other firms fail. However, since the choice of responding
to new scientific insights is arguably endogenous to other firm-level variables, the analysis
in this paper should be interpreted as purely descriptive. In ongoing work we perform an
instrumental variable analysis where we predict a firm’s response to a discovery by looking
at a firm’s propensity to cite prior related work in the period preceding the paper’s publi-
cation. First stage results suggest that this ex-ante information on firm’s patenting is highly
informative of a firm’s propensity to respond.
References


Appendix

Proofs

The investor’s filtering problem

The properties of log-normal distributions allow us to write the expectation term as:

\[ E_t^{\Sigma,1} \left[ e^{(1-\alpha)\eta_{s,t}} \right] = \exp \left\{ (1-\alpha) E_s^{\Sigma,1} t + \frac{(1-\alpha)^2}{2} V^{\Sigma,1} \right\} = \]

\[ = \exp \left\{ (1-\alpha) \lambda^\Sigma V_{s,t} + \frac{(1-\alpha)^2}{2} V^{\Sigma,1} + (1-\alpha) \rho \left[ 1 - \lambda^\Sigma \right] \eta_{s,t-1} + (1-\alpha) \lambda^\Sigma \left[ \epsilon^\eta_{s,t} + \epsilon^\omega_{s,t} \right] \right\}. \]

Hence, the current level of technology can be written as (up to costant terms):

\[ A_{s,t} \propto \left\{ K_s e^{(1-\alpha)\lambda^\Sigma V_{s,t} + (1-\alpha)\rho [1-\lambda^\Sigma] \eta_{s,t-1} + (1-\alpha) \lambda^\Sigma \left[ \epsilon^\eta_{s,t} + \epsilon^\omega_{s,t} \right]} \right\}^{\frac{1}{\varphi-1+\alpha}} \times e^\eta_{s,t} \left( \frac{A_{s,t-1}^{b\phi}}{A_{s,t-1}^{\phi-1+\alpha-b\phi}} \right)^{\frac{1}{\varphi-1+\alpha}}. \]

Given this, we can compute the expected rental rate of capital. Up to constant terms, we obtain:

\[ E^{k,1}[R_{s,t}] = E^{k,1} \left[ \alpha \left( \frac{A_{s,t}}{K_{s,t}} \right)^{(1-\alpha)} \right] \propto \]

\[ E^{k,1} K_{s,t}^{(1-\alpha)(\phi-1)} \left( \frac{A_{s,t-1}^{b\phi}}{A_{s,t-1}^{\phi-1+\alpha-b\phi}} \right)^{\frac{1-\alpha}{\phi-1+\alpha}} \exp \left\{ (1-\alpha) \lambda^\Sigma V_{s,t} \right\} E_{s,t}. \]

In the above expression, \( E_{s,t} \) includes all terms that are not known by the investor at the time of taking his allocation decision:

\[ E_{s,t} = \exp \left\{ \frac{(1-\alpha)}{\phi-1+\alpha} \rho \left[ 1 - \lambda^\Sigma \right] \eta_{s,t-1} + \frac{(1-\alpha)}{\phi-1+\alpha} \lambda^\Sigma \left[ \epsilon^\eta_{s,t} + \epsilon^\omega_{s,t} \right] + \eta_{s,t} \right\}. \]

The posterior distribution of all the relevant variables was computed in the previous subsection, except for \( \epsilon^\eta_{s,t} = \eta_{s,t} - \rho \eta_{s,t-1} \). Also, we have not computed the smoothed value of \( \eta_{s,t-1} \) the investor must use to compute this expectation. The smoothed distribution of \( \eta_{s,t-1} \) given \( \nu_{s,t} \) is given by:

\[ \tilde{\eta}_{s,t-1}^{k,1} \sim N \left( \tilde{E}_{s,t}^{k,1}, \tilde{V}_{s,t}^{k,1} \right), \]

39
where \( \tilde{E}_{s,t}^{k,1} = E_t^{k,1} \left[ \eta_{s,t-1} | \eta_{s,t-1}^{k,2}, \nu_{s,t} \right] \). Letting \( J = \frac{v_{k,2}^2 \rho}{\phi^2 v_{k,2} + \sigma_{\eta}^2} \), the Kalman smoother delivers:

\[ \tilde{E}_{s,t}^{k,2} = E_t^{k,2} + J \left[ E_t^{k,1} - \rho E_{t-1}^{k,2} \right] \]

\[ \Psi^{k,1} = \frac{V_{k,1}}{J^2} \left[ \frac{V_{k,1}^{\phi^2 V_{k,2} + \sigma_{\eta}^2}}{\phi^2 V_{k,2} + \sigma_{\eta}^2} \right]. \]

Hence:

\[ E_t^{k,1} [\mathcal{E}_{s,t}] \propto \exp \left\{ \frac{(1 - \alpha)}{\phi - 1 + \alpha} \rho \left[ 1 - \lambda_v^{\Sigma} - \lambda_{o^{\Sigma}} \right] \eta_{s,t-1} + \left[ \frac{(1 - \alpha)}{\phi - 1 + \alpha} \lambda_{o^{\Sigma}} + 1 \right] \eta_{s,t} + \left[ \frac{(1 - \alpha)}{\phi - 1 + \alpha} \lambda_{o^{\Sigma}} \right] \epsilon_{s,t}^{\omega} \right\}. \]

Taking expectations with respect to the information set of the investor yields (again, neglecting constant terms):

\[ E_t^{k,1} [\mathcal{E}_{s,t}] \propto \exp \left\{ \frac{(1 - \alpha)}{\phi - 1 + \alpha} \rho \left[ 1 - \lambda_v^{\Sigma} - \lambda_{o^{\Sigma}} \right] \tilde{E}_{s,t}^{k,1} + \left[ \frac{(1 - \alpha)}{\phi - 1 + \alpha} \lambda_{o^{\Sigma}} + 1 \right] E_{s,t}^{k,1} \right\}. \]

Finally, the capital allocation decision in a non-degenerate equilibrium in which both sectors are active can be described by (3.9), from which Proposition 1 follows.

The realized rental price of capital will be:

\[ R_{s,t} = \alpha K_{s,t} \frac{(1 - \alpha)^{\phi - 1 + \alpha}}{\phi - 1 + \alpha} \left[ \frac{A_{s,t-1}}{A_{s,t-1}} \right]^{\frac{(1 - \alpha)}{\phi - 1 + \alpha}} \times \exp \left\{ \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda_v^{\Sigma} \nu_{s,t} \right\} \times \exp \left\{ \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \left[ 1 - \lambda_v^{\Sigma} \right] + (1 - \alpha) \right\} \rho \eta_{s,t-1} \times \exp \left\{ \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda_{o^{\Sigma}} e_{s,t}^{\omega} \right\} \times \exp \left\{ \frac{(1 - \alpha)}{\phi - 1 + \alpha} \lambda_{o^{\Sigma}} + (1 - \alpha) \right\} \epsilon_{s,t}^{\eta}. \]

Conditional on the past information the investor has, observing \( R_{s,t} \) will convey an additional signal in the following form:

\[ \tilde{r}_{s,t} = \left( \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \left[ 1 - \lambda_v^{\Sigma} \right] + (1 - \alpha) \right) \rho \eta_{s,t-1} + \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda_{o^{\Sigma}} e_{s,t}^{\omega} + \left( \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda_{o^{\Sigma}} + (1 - \alpha) \right) \epsilon_{s,t}^{\eta}. \]
The signal extraction problem at the end of the period takes the following form:

\[
\begin{bmatrix}
\eta_{s,t}^k \\
v_{s,t} \\
\bar{r}_{s,t}
\end{bmatrix} 
\sim N
\left(
\begin{bmatrix}
\rho E_{s,t-1}^{k,2} \\
\rho E_{s,t-1}^{k,2} \\
C_1 \rho E_{s,t-1}^{k,2}
\end{bmatrix} , \mathcal{V}\right)
\]

where:

\[
\mathcal{V} = 
\begin{bmatrix}
\rho^2 V^{k,2} + \sigma^2 \eta & \rho^2 V^{k,2} + \sigma^2 \nu & C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta \\
\rho^2 V^{k,2} + \sigma^2 \nu & \rho^2 V^{k,2} + \sigma^2 \nu + \sigma^2 \nu & C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta \\
C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta & C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \nu & C_1 \rho^2 V^{k,2} + C_2 \sigma^2 \nu + C_3 \sigma^2 \eta
\end{bmatrix}
\]

and

\[
C_1 = \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \left[ 1 - \lambda \Sigma \right] + (1 - \alpha) \\
C_2 = \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda \Sigma \\
C_3 = \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda \Sigma + (1 - \alpha)
\]

Given this, we can solve for the conditional distribution of \( \eta_{s,t}^k \):

\[
\eta_{s,t}^k \sim N \left( \rho E_{s,t}^{k,2} , V^{k,2} \right)
\]

where:

\[
E_{s,t}^{k,2} = \rho E_{s,t-1}^{k,2} + \left[ \rho^2 V^{k,2} + \sigma^2 \eta \right] \times
\begin{bmatrix}
\rho^2 V^{k,2} + \sigma^2 \eta & \rho^2 V^{k,2} + C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta \\
\rho^2 V^{k,2} + \sigma^2 \nu & \rho^2 V^{k,2} + \sigma^2 \nu + \sigma^2 \nu & C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta \\
C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta & C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \nu & C_1 \rho^2 V^{k,2} + C_2 \sigma^2 \nu + C_3 \sigma^2 \eta
\end{bmatrix}^{-1} 
\begin{bmatrix}
v_{s,t} - \rho E_{s,t-1}^{k,2} \\
v_{s,t} - \rho E_{s,t-1}^{k,2} \\
\bar{r}_{s,t} - C_1 \rho E_{s,t-1}^{k,2}
\end{bmatrix}
\]

and

\[
V^{k,2} = \rho^2 V^{k,2} + \sigma^2 \eta - \left[ \rho^2 V^{k,2} + \sigma^2 \eta \right] \times
\begin{bmatrix}
\rho^2 V^{k,2} + \sigma^2 \eta & \rho^2 V^{k,2} + C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta \\
\rho^2 V^{k,2} + \sigma^2 \nu & \rho^2 V^{k,2} + \sigma^2 \nu + \sigma^2 \nu & C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta \\
C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta & C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \nu & C_1 \rho^2 V^{k,2} + C_2 \sigma^2 \nu + C_3 \sigma^2 \eta
\end{bmatrix}^{-1} 
\begin{bmatrix}
\rho^2 V^{k,2} + \sigma^2 \eta \\
\rho^2 V^{k,2} + C_1 \rho^2 V^{k,2} + C_3 \sigma^2 \eta \\
C_1 \rho^2 V^{k,2} + C_2 \sigma^2 \nu + C_3 \sigma^2 \eta
\end{bmatrix}
\]

Solving for the fixed point of \( V^{k,2} \) delivers the steady state Kalman filter residual variance of \( \eta_{s,t}^k \).
Proof of Proposition 2

Consider an unperturbed economy in which \( \frac{A_{1,t}}{A_{2,t}} > 1 \) (the case \( \frac{A_{1,t}}{A_{2,t}} < 1 \) is analogous). We want to derive conditions under which

\[
\frac{A_{2,t}}{A_{1,t}} < \frac{A_{1,t+1}}{A_{2,t+1}} < \frac{A_{1,t}}{A_{2,t}}. 
\]  

(A.1)

Since the economy is unperturbed, we must have \( \frac{R_{1,t+1}}{A_{2,t+1}} = \frac{R_{2,t+1}}{A_{1,t+1}} \) or, equivalently, \( \frac{K_{1,t+1}}{A_{1,t+1}} = \frac{1-K_{1,t+1}}{A_{2,t+1}} = R_{t+1} \), which implies:

\[
\sigma_{s,t} = \left\{ \left(1 - \alpha\right) A_{s,t-1}^{\alpha} A_{s,t-1}^{b} \bar{R}_{t+1} \right\}^{\frac{1}{\phi-1}}. 
\]

Hence, the law of motion for \( \frac{A_{1,t+1}}{A_{2,t+1}} \) can be written as:

\[
\frac{A_{1,t+1}}{A_{2,t+1}} = \left(\frac{A_{1,t}}{A_{2,t}}\right)^{\frac{a-\alpha}{\phi-1}}. 
\]

Since we assumed \( \frac{A_{1,t}}{A_{2,t}} > 1 \), in order to have \( \frac{A_{1,t+1}}{A_{2,t+1}} < \frac{A_{1,t}}{A_{2,t}} \) we need the following restriction:

\[
b > \frac{\alpha}{2\phi}, 
\]

while to have \( \frac{A_{2,t}}{A_{1,t}} < \frac{A_{1,t+1}}{A_{2,t+1}} \) we need

\[
b < \frac{\alpha + 2(\phi-1)}{2\phi}. 
\]

On Proposition 3

1. Consider first a fundamental shock \( \epsilon_{1,t}^f = u > 0 \). Clearly, \( \eta_{s,t} = \nu_{s,t} = u \). Capital is allocated according to:

\[
\left[ \frac{K_{1,t}}{1-K_{1,t}} \right] = \exp \left\{ \left( \frac{(1-\alpha) \lambda_{0}^{\Sigma} + (\phi - 1 + \alpha)}{(\phi - 1)} \right) \frac{\rho^{2}V^{k,2} + \sigma_{\eta}^{2}}{\rho^{2}V^{k,2} + \sigma_{\bar{\eta}}^{2} + \sigma_{\bar{\nu}}^{2}} + \frac{\lambda_{0}^{\Sigma}}{(\phi - 1)} \right\} u. 
\]

Now, consider the ratio \( \frac{R_{1,t}}{R_{2,t}} \) at the end of the period:

\[
\frac{R_{1,t}}{R_{2,t}} = \left( \frac{1-K_{1,t}}{K_{1,t}} \times \frac{A_{1,t}}{A_{2,t}} \right)^{(1-\alpha)} = \left( \frac{1-K_{1,t}}{K_{1,t}} \times \frac{\sigma_{1,t}^{e}u}{\sigma_{2,t}} \right)^{(1-\alpha)} = 
\]

42
Suppose $\frac{R_{1,t}}{\Sigma^2_t} < 1$, then:

$$
\left\{ \begin{array}{l}
\left( \frac{K_{1,t}}{1-K_{1,t}} \right)^{-(\gamma-1)} \times \exp \left\{ (1-\alpha) \left[ 1 + \frac{(1-\alpha)}{\phi-1+\alpha} \left[ \lambda^2 + \lambda^2 \right] u \right] \right. \\
\end{array} \right.
$$

$$
\equiv \left( \frac{(1-\alpha) \lambda^2 + (\phi-1+\alpha)}{(\phi-1)} \right) \frac{\rho^2 V^k + \sigma^2}{\rho^2 V^k + \sigma^2} + \frac{\lambda^2}{(\phi-1)} > \phi-1+\alpha
$$

$$
\Rightarrow \left\{ (1-\alpha) \lambda^2 + (\phi-1+\alpha) \left[ 1 + \frac{(1-\alpha)}{\phi-1+\alpha} \left[ \lambda^2 + \lambda^2 \right] \right] \right. \\
$$

which suggests the response of the rental rate of capital is negative when, given the other variances, $\sigma^2$ is sufficiently large. The intuition is that when $\sigma^2$ is small, the investor trusts the signal, but if $\sigma^2$ is large enough, the innovator will not trust the signal anyway, and they will not respond by innovating enough. This is reflected in the positive cross derivative of $\sigma^2$ and $\sigma^2$, which produces a larger drop in the right-hand side, the larger the value of $\sigma^2$. In summary, the response of the rental price of capital is positive after a fundamental shock if $\sigma^2$ is
sufficiently large, given $\sigma_\eta^2$ and $\sigma_\omega^2$.

2. Now, consider a noise shock $\varepsilon_{1,t} = u$. The allocation of capital is the same as in the previous case:

$$\left[ \frac{K_{1,t}}{1 - K_{1,t}} \right] = \exp \left\{ \left[ \frac{(1 - \alpha) \lambda_\omega^2 + (\phi - 1 + \alpha)}{(\phi - 1)} \right] \frac{\rho^2 V^{k,2} + \sigma_\eta^2}{\rho^2 V^{k,2} + \sigma_\eta^2 + \sigma_\nu^2} + \frac{\lambda_\nu^2}{(\phi - 1) u} \right\}.$$

Now, consider the ratio $\frac{R_{1,t}}{R_{2,t}}$ at the end of the period:

$$\frac{R_{1,t}}{R_{2,t}} = \left( \frac{1 - K_{1,t}}{K_{1,t}} \times \frac{A_{1,t}}{A_{2,t}} \right)^{(1 - \alpha)} = \left( \frac{1 - K_{1,t}}{K_{1,t}} \times \frac{\sigma_{1,t}}{\sigma_{2,t}} \right)^{(1 - \alpha)} = \left( \frac{1 - K_{1,t}}{K_{1,t}} \right)^{(1 - \alpha)} \times \left\{ \frac{K_{1,t}}{(1 - K_{1,t})} \right\}^{a(1 - \alpha) \frac{\phi - 1 + \alpha}{\phi - 1 + \alpha}} \times \left\{ \frac{E_{1,t}}{E_{1,t}} \right\}^{1 - \frac{\alpha}{\phi - 1 + \alpha}} \times \left\{ \frac{\lambda_\nu^2}{1 - \phi} \right\} \times \left\{ \exp \left\{ \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda_\nu^2 u \right\} \right\}.$$

Now, assume that $\frac{R_{1,t}}{R_{2,t}} > 1$, that is:

$$\left\{ \frac{K_{1,t}}{1 - K_{1,t}} \right\}^{-\frac{(\phi - 1)(1 - \alpha)}{\phi - 1 + \alpha}} \times \left\{ \exp \left\{ \frac{(1 - \alpha)^2}{\phi - 1 + \alpha} \lambda_\nu^2 u \right\} \right\} > 1$$

$$\Leftrightarrow \left( \frac{(1 - \alpha) \lambda_\omega^2 + (\phi - 1 + \alpha)}{(\phi - 1)} \right) \frac{\rho^2 V^{k,2} + \sigma_\eta^2}{\rho^2 V^{k,2} + \sigma_\eta^2 + \sigma_\nu^2} + \frac{\lambda_\nu^2}{(\phi - 1) \lambda_\nu^2} < \frac{(1 - \alpha)}{(\phi - 1) \lambda_\nu^2},$$

which is clearly impossible, since $(1 - \alpha) < 1$. Hence, after a noise shock $\varepsilon_{1,t}$, the relative rate of return on capital in the sector hit by the shock drops on impact.
Data Appendix

Classification:

<table>
<thead>
<tr>
<th>Micro Class</th>
<th>Macro Class</th>
<th>Micro Class</th>
<th>Macro Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural Economics &amp; Policy</td>
<td>A</td>
<td>Endocrinology &amp; Metabolism</td>
<td>M</td>
</tr>
<tr>
<td>Agriculture, Dairy &amp; Animal Science</td>
<td>A</td>
<td>Gastroenterology &amp; Hepatology</td>
<td>M</td>
</tr>
<tr>
<td>Agricultural Engineering</td>
<td>A</td>
<td>Geriatrics &amp; Gerontology</td>
<td>M</td>
</tr>
<tr>
<td>Agriculture, Multidisciplinary</td>
<td>A</td>
<td>Health Care Sciences &amp; Services</td>
<td>M</td>
</tr>
<tr>
<td>Agronomy</td>
<td>A</td>
<td>Hematology</td>
<td>M</td>
</tr>
<tr>
<td>Biodiversity Conservation</td>
<td>A</td>
<td>Immunology</td>
<td>M</td>
</tr>
<tr>
<td>Ecology</td>
<td>A</td>
<td>Infectious Diseases</td>
<td>M</td>
</tr>
<tr>
<td>Environmental Sciences</td>
<td>A</td>
<td>Integrative &amp; Complementary Medicine</td>
<td>M</td>
</tr>
<tr>
<td>Fisheries</td>
<td>A</td>
<td>Medical Ethics</td>
<td>M</td>
</tr>
<tr>
<td>Food Science &amp; Technology</td>
<td>A</td>
<td>Medical Informatics</td>
<td>M</td>
</tr>
<tr>
<td>Forestry</td>
<td>A</td>
<td>Medical Laboratory Technology</td>
<td>M</td>
</tr>
<tr>
<td>Horticulture</td>
<td>A</td>
<td>Medicine, General &amp; Internal</td>
<td>M</td>
</tr>
<tr>
<td>Mycology</td>
<td>A</td>
<td>Medicine, Legal</td>
<td>M</td>
</tr>
<tr>
<td>Ornithology</td>
<td>A</td>
<td>Medicine, Research &amp; Experimental</td>
<td>M</td>
</tr>
<tr>
<td>Parasitology</td>
<td>A</td>
<td>Neurosciences</td>
<td>M</td>
</tr>
<tr>
<td>Plant Sciences</td>
<td>A</td>
<td>Nursing</td>
<td>M</td>
</tr>
<tr>
<td>Zoology</td>
<td>A</td>
<td>Nutrition &amp; Dietetics</td>
<td>M</td>
</tr>
<tr>
<td>Biochemical Research Methods</td>
<td>B</td>
<td>Obstetrics &amp; Gynecology</td>
<td>M</td>
</tr>
<tr>
<td>Biochemistry &amp; Molecular Biology</td>
<td>B</td>
<td>Oncology</td>
<td>M</td>
</tr>
<tr>
<td>Biology</td>
<td>B</td>
<td>Ophthalmology</td>
<td>M</td>
</tr>
<tr>
<td>Biophysics</td>
<td>B</td>
<td>Orthopedics</td>
<td>M</td>
</tr>
<tr>
<td>Biotechnology &amp; Applied Microbiology</td>
<td>B</td>
<td>Otorhinolaryngology</td>
<td>M</td>
</tr>
<tr>
<td>Cell Biology</td>
<td>B</td>
<td>Pathology</td>
<td>M</td>
</tr>
<tr>
<td>Developmental Biology</td>
<td>B</td>
<td>Pediatrics</td>
<td>M</td>
</tr>
<tr>
<td>Entomology</td>
<td>B</td>
<td>Peripheral Vascular Diseases</td>
<td>M</td>
</tr>
<tr>
<td>Evolutionary Biology</td>
<td>B</td>
<td>Pharmacology &amp; Pharmacy</td>
<td>M</td>
</tr>
<tr>
<td>Genetics &amp; Heredity</td>
<td>B</td>
<td>Physiology</td>
<td>M</td>
</tr>
<tr>
<td>Marine &amp; Freshwater Biology</td>
<td>B</td>
<td>Psychiatry</td>
<td>M</td>
</tr>
<tr>
<td>Mathematical &amp; Computational Biology</td>
<td>B</td>
<td>Psychology</td>
<td>M</td>
</tr>
<tr>
<td>Microbiology</td>
<td>B</td>
<td>Environmental &amp; Occupational Health</td>
<td>M</td>
</tr>
<tr>
<td>Reproductive Biology</td>
<td>B</td>
<td>Radiology &amp; Medical Imaging</td>
<td>M</td>
</tr>
<tr>
<td>Micro Class</td>
<td>Macro Class</td>
<td>Micro Class</td>
<td>Macro Class</td>
</tr>
<tr>
<td>-------------------------------------------------</td>
<td>-------------</td>
<td>----------------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Chemistry, Analytical</td>
<td>C</td>
<td>Rehabilitation</td>
<td>M</td>
</tr>
<tr>
<td>Chemistry, Applied</td>
<td>C</td>
<td>Respiratory System</td>
<td>M</td>
</tr>
<tr>
<td>Chemistry, Medicinal</td>
<td>C</td>
<td>Rheumatology</td>
<td>M</td>
</tr>
<tr>
<td>Chemistry, Multidisciplinary</td>
<td>C</td>
<td>Substance Abuse</td>
<td>M</td>
</tr>
<tr>
<td>Chemistry, Inorganic &amp; Nuclear</td>
<td>C</td>
<td>Surgery</td>
<td>M</td>
</tr>
<tr>
<td>Chemistry, Organic</td>
<td>C</td>
<td>Toxicology</td>
<td>M</td>
</tr>
<tr>
<td>Chemistry, Physical</td>
<td>C</td>
<td>Transplantation</td>
<td>M</td>
</tr>
<tr>
<td>Electrochemistry</td>
<td>C</td>
<td>Tropical Medicine</td>
<td>M</td>
</tr>
<tr>
<td>Mineralogy</td>
<td>C</td>
<td>Urology &amp; Nephrology</td>
<td>M</td>
</tr>
<tr>
<td>Automation &amp; Control Systems</td>
<td>E</td>
<td>Veterinary Sciences</td>
<td>M</td>
</tr>
<tr>
<td>Construction &amp; Building Technology</td>
<td>E</td>
<td>Virology</td>
<td>M</td>
</tr>
<tr>
<td>Energy &amp; Fuels</td>
<td>E</td>
<td>Crystallography</td>
<td>N</td>
</tr>
<tr>
<td>Engineering, Aerospace</td>
<td>E</td>
<td>Nanoscience &amp; Nanotechnology</td>
<td>N</td>
</tr>
<tr>
<td>Engineering, Biomedical</td>
<td>E</td>
<td>Spectroscopy</td>
<td>N</td>
</tr>
<tr>
<td>Engineering, Chemical</td>
<td>E</td>
<td>Acoustics</td>
<td>O</td>
</tr>
<tr>
<td>Engineering, Civil</td>
<td>E</td>
<td>Imaging Science &amp; Photogr. Tech.</td>
<td>O</td>
</tr>
<tr>
<td>Engineering, Electrical &amp; Electronic</td>
<td>E</td>
<td>Microscopy</td>
<td>O</td>
</tr>
<tr>
<td>Engineering, Environmental</td>
<td>E</td>
<td>Neuroimaging</td>
<td>O</td>
</tr>
<tr>
<td>Engineering, Geological</td>
<td>E</td>
<td>Optics</td>
<td>O</td>
</tr>
<tr>
<td>Engineering, Industrial</td>
<td>E</td>
<td>Mathematics</td>
<td>P</td>
</tr>
<tr>
<td>Engineering, Manufacturing</td>
<td>E</td>
<td>Mathematics, Interdisciplinary Applications</td>
<td>P</td>
</tr>
<tr>
<td>Engineering, Marine</td>
<td>E</td>
<td>Mechanics</td>
<td>P</td>
</tr>
<tr>
<td>Engineering, Mechanical</td>
<td>E</td>
<td>Physics, Applied</td>
<td>P</td>
</tr>
<tr>
<td>Engineering, Petroleum</td>
<td>E</td>
<td>Physics, Atomic, Molecular &amp; Chemical</td>
<td>P</td>
</tr>
<tr>
<td>Engineering, Ocean</td>
<td>E</td>
<td>Physics, Condensed Matter</td>
<td>P</td>
</tr>
<tr>
<td>Instruments &amp; Instrumentation</td>
<td>E</td>
<td>Physics, Fluids &amp; Plasmas</td>
<td>P</td>
</tr>
<tr>
<td>Metallurgy &amp; Metallurgical Engineering</td>
<td>E</td>
<td>Physics, Mathematical</td>
<td>P</td>
</tr>
<tr>
<td>Mining &amp; Mineral Processing</td>
<td>E</td>
<td>Physics, Multidisciplinary</td>
<td>P</td>
</tr>
<tr>
<td>Nuclear Science &amp; Technology</td>
<td>E</td>
<td>Physics, Nuclear</td>
<td>P</td>
</tr>
<tr>
<td>Robotics</td>
<td>E</td>
<td>Physics, Particles &amp; Fields</td>
<td>P</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>E</td>
<td>Statistics &amp; Probability</td>
<td>P</td>
</tr>
<tr>
<td>Transportation Science &amp; Technology</td>
<td>E</td>
<td>Thermodynamics</td>
<td>P</td>
</tr>
<tr>
<td>Micro Class</td>
<td>Macro Class</td>
<td>Micro Class</td>
<td>Macro Class</td>
</tr>
<tr>
<td>-------------------------------------</td>
<td>-------------</td>
<td>---------------------------------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Astronomy &amp; Astrophysics</td>
<td>G</td>
<td>Computer Science, Artificial Intelligence</td>
<td>S</td>
</tr>
<tr>
<td>Geochemistry &amp; Geophysics</td>
<td>G</td>
<td>Computer Science, Cybernetics</td>
<td>S</td>
</tr>
<tr>
<td>Geography, Physical</td>
<td>G</td>
<td>Computer Science, Hardware &amp; Architecture</td>
<td>S</td>
</tr>
<tr>
<td>Geology</td>
<td>G</td>
<td>Computer Science, Information Systems</td>
<td>S</td>
</tr>
<tr>
<td>Geosciences, Multidisciplinary</td>
<td>G</td>
<td>Computer Science, Interd. App.</td>
<td>S</td>
</tr>
<tr>
<td>Limnology</td>
<td>G</td>
<td>Computer Science, Software Engineering</td>
<td>S</td>
</tr>
<tr>
<td>Meteorology &amp; Atmospheric Sciences</td>
<td>G</td>
<td>Computer Science, Theory &amp; Methods</td>
<td>S</td>
</tr>
<tr>
<td>Oceanography</td>
<td>G</td>
<td>Materials Science, Biomaterials</td>
<td>T</td>
</tr>
<tr>
<td>Paleontology</td>
<td>G</td>
<td>Materials Science, Ceramics</td>
<td>T</td>
</tr>
<tr>
<td>Remote Sensing</td>
<td>G</td>
<td>Materials Science, Characterization, Testing</td>
<td>T</td>
</tr>
<tr>
<td>Soil Science</td>
<td>G</td>
<td>Materials Science, Coatings &amp; Films</td>
<td>T</td>
</tr>
<tr>
<td>Water Resources</td>
<td>G</td>
<td>Materials Science, Composites</td>
<td>T</td>
</tr>
<tr>
<td>Allergy</td>
<td>M</td>
<td>Materials Science, Multidisciplinary</td>
<td>T</td>
</tr>
<tr>
<td>Anatomy &amp; Morphology</td>
<td>M</td>
<td>Materials Science, Paper &amp; Wood</td>
<td>T</td>
</tr>
<tr>
<td>Andrology</td>
<td>M</td>
<td>Materials Science, Textiles</td>
<td>T</td>
</tr>
<tr>
<td>Anesthesiology</td>
<td>M</td>
<td>Polymer Science</td>
<td>T</td>
</tr>
<tr>
<td>Cardiac &amp; Cardiovascular System</td>
<td>M</td>
<td>Behavioral Sciences</td>
<td>Z</td>
</tr>
<tr>
<td>Clinical Neurology</td>
<td>M</td>
<td>Education, Scientific Disciplines</td>
<td>Z</td>
</tr>
<tr>
<td>Critical Care Medicine</td>
<td>M</td>
<td>History &amp; Philosophy of Science</td>
<td>Z</td>
</tr>
<tr>
<td>Dentistry, Oral Surgery &amp; Medicine</td>
<td>M</td>
<td>Multidisciplinary Sciences</td>
<td>Z</td>
</tr>
<tr>
<td>Emergency Medicine</td>
<td>M</td>
<td>Sport Sciences</td>
<td>Z</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Macro Class</th>
<th>Symbol</th>
<th>Macro Class</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, Food, Zoology</td>
<td>A</td>
<td>Nanoscience</td>
<td>N</td>
</tr>
<tr>
<td>Life Sciences</td>
<td>B</td>
<td>Optics/Acoustics</td>
<td>O</td>
</tr>
<tr>
<td>Chemistry</td>
<td>C</td>
<td>Physics / Mathematics</td>
<td>P</td>
</tr>
<tr>
<td>Engineering</td>
<td>E</td>
<td>Computer Science</td>
<td>S</td>
</tr>
<tr>
<td>Geography/Astronomy</td>
<td>G</td>
<td>Materials Science</td>
<td>T</td>
</tr>
<tr>
<td>Medicine</td>
<td>M</td>
<td>Others</td>
<td>Z</td>
</tr>
</tbody>
</table>

47
Figure A.1: Cumulative response of Physical Capital (PPEGT) in percentage change from their value at 0, following a one standard-deviation shock to the response measure. The figure shows point estimates and 90% error bands. Standard errors are clustered at the firm level. The regressions include (2-digit SIC) industry-time fixed effects, and control for the lagged value of total assets (or employment), the logarithm of the number of patents and firm’s profitability (ROA). The left panel includes lags of response up to $T = 4$, the right panel includes up to $T = 8$.

Figure A.2: Cumulative response of Physical Capital (PPEGT) in percentage change from their value at 0, following a one standard-deviation shock to the response measure. The figure shows point estimates and 90% error bands. Standard errors are clustered at the firm level. The left panel includes (2-digit SIC) industry-time fixed effects but only controls for the current log of the stock of patents, and hence includes entry observations (that are normalized to +2). The right panel includes (2-digit SIC) industry-time fixed effects, and control for the lagged value of total assets (or employment), the logarithm of the number of patents and firm’s profitability (ROA) and conditions on non-exit observations (excludes $\Delta\% = -2$).