Uncertainty and Innovation
During the Great Depression

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Abstract

We examine research investment behavior during the Great Depression using a Bayesian model of innovation under uncertainty and new data on corporate R&D. Exploiting an increase in sector versus aggregate uncertainty during the 1930s, we show that firms with imprecise sector-level priors on payoffs to innovation updated their beliefs and responded stronger to sector-level signals than firms holding more precise priors. The updating component we specify is most pronounced in the early years of the Depression and is robust to measures of firm size and liquidity. Learning and updating effects are strongest in high uncertainty, consumer durables and intermediate good sectors.

JEL: C11, D8, D21, O3
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1 Introduction

The Great Depression represents one of the most significant adverse shocks to US economic activity, yet we know very little about how it affected firm-level behavior.\footnote{Ours is one of only a few papers that studies the Great Depression from a firm-level perspective. Others have focused on particular industries such as Klepper and Simons (2000) who study industry evolution in the tire industry at this time or Raff and Bresnahan (1991) who examine the shakeout of firms in motor vehicle manufacturing. A much larger macro literature uses general equilibrium frameworks to study the Depression. See for example, Temin (1989), Bordo, Erceg and Evan (2000), Chari, Kehoe and McGrattan (2003), Christiano, Motto, and Rostagno (2003), Cole and Ohanian (2004).} In this paper we examine how the appreciable increase in uncertainty following the stock market crash of 1929 (Merton, 1987; Schwert, 1989; Romer, 1990; White, 1990; Bloom, 2009) influenced the timing of R&D, a key driver of technological change and economic growth (Aghion and Howitt, 1992). In normal times there is uncertainty about the payoff to innovation, deriving from uncertainty about the impact of the innovation as well as about the timing of research success. At the time of the Great Depression, overlaid onto this was high uncertainty regarding demand (Temin, 1976, 1989). We propose a model for the research investment decision of firms at times of high uncertainty and use it to examine a new, comprehensive dataset of US corporate R&D.

At the core of our approach is a simple Bayesian idea that firms update their information set based on the signals they observe and they alter their research investment decisions in line with the extent to which they update their priors. R&D, as proxied by early stage patenting activity, was highly cyclical during the Depression (Figure 1), but there was strong variation across sectors as some innovations were advanced while others were held back (Figure 2). We show that sectors in which firms have tight prior distributions on the payoff to innovation are likely to experience less of a change in R&D in response to the observed signal compared to sectors in which firms operate with diffuse, or high variance, prior distributions on payoffs. We find strong support in the data for this updating mechanism as an influence on research investment decisions.

Our theory is developed in light of a change in the structure of uncertainty during the Great Depression. At the aggregate level Schwert (1989) shows that uncertainty reached unprecedented levels between 1929 and 1940 with the standard deviation of monthly stock returns being in excess of 20 percent in 1932. Merton (1987) and Voth (2005) view the rise in stock market volatility to be causally related to fears about capitalism’s survival.\footnote{Mankiw (2006, p.29) states that the Depression “was an economic downturn of unprecedented scale, including incomes so depressed and unemployment so widespread that it is no exaggeration to say that the viability of the capitalist system was called in question.” Joseph Schumpeter (1941, p.352) described the Great Depression as being “catastrophic.”} Although aggregate uncertainty was high, we also note that sector-level uncertainty rose relatively as measured by stock market volatility in two-digit SIC codes (Figure 3). In our model a change in the structure of uncertainty magnifies a signal extraction problem whereby firms need to distinguish between permanent sector-level
changes and aggregate disturbances as they determine their expected payoffs to innovation and their optimal investment in R&D.

We test our theory using a newly constructed firm-level dataset covering the entire interwar US corporate research and development sector. Our firms come from the National Research Council’s (NRC) direct correspondence survey of US industrial research labs in the years 1921, 1927, 1931, 1933 and 1938. An attractive property of the data is its comprehensive coverage of corporate R&D with large, small, traded and non-publicly traded firms included. The firms the NRC surveyed contributed disproportionately to productivity advance with real expenditure on R&D more than doubling during the 1930s (Mowery and Rosenberg, 1989, p.69). Our dataset consists of 2,777 individual firms with in-house R&D facilities. A downside is that, unlike for the modern era when R&D statistics are collected on an annual basis, the historical NRC data only reflect snapshots of R&D activity as opposed to observations for a full time series of years.

We overcome this problem using hand-matched patent application data, giving an annual metric of R&D related activity. Innovation is a multi-stage process and by using patents as of their application date we are observing inventive activity at an initial phase of research and development (Griliches, 1990). In their taxonomy of the innovation process Francois and Lloyd-Ellis (2008) label the type of patents that we observe as “R&D”. We also observe patents that developed into useful technologies by distinguishing high quality patents using a new dataset containing 42.8 million historical patent citations. These represent references to previous patents from US patents granted between 1947 and 2008. Historical citations capture the economic significance of inventions, providing a retrospective measure of patent quality.

We show that the uncertainty shock of the Great Depression changed R&D behavior. While the aggregate data in Figure 1 show a large drop and delay in patenting activity, which is consistent with the “cautionary effects” of uncertainty on partially irreversible investment (Dixit and Pindyck, 1994), we also show that the aggregate data mask considerable variation in patenting by sector. We examine the causes of this change using empirical specifications derived from our updating model and find large differences in patenting across the sectoral uncertainty distribution. Citation-weighted patent applications are 23 percent lower when moving from the 10th to the 90th percentile of sectoral uncertainty. The learning and updating effects we detect are substantial and vary considerably over the life cycle of the Great Depression: they are particularly concentrated in the downturn of 1930 to 1932 and disappear in most of our specifications during the recovery phase of 1933 to 1936.

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3 While patents are an imperfect measure of technological development they are strongly correlated with R&D and productivity (Griliches, 1990; Bloom and Van Reenen, 2002).

4 1947 is the first year references were made explicitly on patent documents. We thank James Ryley (President) and David Hawley (Director of R&D) of FreePatentsOnline.com who supplied 5.1 million XML files used for the 1947-2008 citations and to Sarah Woolverton from Research Computing Services at Harvard Business School for processing these data.
Our main results are robust to including matching firm-level balance sheet variables from *Moody’s Manual of Industrials*. We rule out firm size as a confounding influence using data on physical capital and also confirm our results are not driven by differences in firm-level financial liquidity. Based on the Schumpeterian view of cycles, Aghion et al. (2005, 2008) show that the reorganization of innovation is related to credit constraints. Tightly constrained firms are less likely to invest in R&D in downturns than unconstrained firms. Although liquidity enters positively and is significant in regressions for the Depression era, the effect of uncertainty through our updating component continues to be statistically and economically significant.

Our analysis is most closely related to Romer (1990) who identifies a large drop in expenditures on consumer durables after 1929. Heightened stock market volatility in the aftermath of the Great Crash raised consumers’ uncertainty about future income, leading to delays in consumer durables purchases until uncertainty was resolved. We argue that the increase in uncertainty following the Great Crash strongly influenced early stage corporate R&D, leading to large differences in research investment across sectors. Our empirical analysis shows that learning and updating as a reaction to uncertainty were particularly strong in sectors affected by consumer durables purchases and are also strong when distinguishing between high and low uncertainty sectors and in intermediate good sectors. Beyond the literature on the Great Depression, our findings are related to works examining the financing of innovation and the dynamics of R&D over the business cycle (e.g., Shleifer, 1986; Fatas, 2000; Francois & Lloyd-Ellis, 2006; Comin and Gertler, 2006; Barlevy, 2007). To the extent that macroeconomic uncertainty shocks and severe economic downturns such as the 1930s are “not just a relic of the past” (Kehoe and Prescott, 2007, p.2), our framework is useful for understanding research investment decisions under conditions of extreme and persistent uncertainty.

In the next section we present historical examples of innovations underlying our model of research investment. Section three presents the basic intuition behind the model. Section four outlines the empirical framework. Section five describes our dataset on R&D firms. Section six discusses the main results and robustness checks. Section seven concludes. The model is presented in the Appendix.

2 The Timing of Depression-Era Innovations

The 1930s was a technologically progressive decade (Field, 2003; Feinstein et al., 2008, p.174) and our model is motivated by the differential timing of key innovations during this period. While Figure 1 shows there was a drop in the growth rate of aggregate patenting during the Great Depression, equally, however, research investment in technological development did not stop in some sectors. For example, Figure 2 illustrates different technology development paths during the
early years of the Depression for firms in chemicals and electrical equipment sectors.

An often-cited example of Depression-era innovation advancing is neoprene (synthetic rubber) introduced by DuPont. In April 1930 a noted DuPont research scientist, Wallace Carothers, recorded the initial discovery of neoprene, which boosted R&D and led to two key US patent applications - 1,950,431 (October 1930) and 1,950,432 (February 1931) - both of which were granted in 1934. DuPont announced neoprene publicly in November 1931 and within three years the firm had invested over $1 million on R&D, with commercial introduction coming in 1937 (Smith, 1985; Scherer, 1989, pp.4-5). This is not an isolated example of corporate research investment progressing in the nadir of the Depression. By 1937, 40 percent of DuPont’s sales came from products that did not exist prior to 1929 such as rayon, enamels and cellulose film (DuPont, Annual Report, 1937, pp.12-13). In another industry - automobiles - Raff and Trajtenberg (1997) see innovation proceeding at a rapid rate, especially in the development of the internal combustion engine.

In other cases innovation was delayed. The television could have been introduced much earlier had firms like RCA, faced with volatility during the 1920s stock market runup and the Great Crash, been more certain about payoffs to technological development (MacLaurin, 1949, p.265). RCA had the technical know-how to push forward with electronic television in 1930 but delayed its million-dollar R&D program until 1935. Similarly the introduction of FM radio was delayed until the mid-1930s even though its superior performance (in terms of lower static) could have led to the replacement of AM radio sets (Szostak, 1995, p.184). In petroleum, catalytic cracking technology for breaking complex hydrocarbons into simpler molecules to produce high grade gasoline was delayed by the Depression, first being introduced in 1937 (Williamson et.al., 1963, p.606). Arguably, the jet engine could have been developed for commercial purposes earlier as the basic underpinning innovations such as titanium alloys existed in 1930 (Constant, 1980).

3 Uncertainty and its Effect on Research Investment

Our empirical work is guided by a simple model of innovation under uncertainty, which we present in detail in an Appendix. This section outlines the main features of the model.

We build on the Aghion-Howitt (1992) multisector framework of quality-improving innovation where technology advances take place from investment in research. We depart from this model by introducing sector-specific uncertainty in the returns to research investment. The approach we use also differs from conventional models of investment under uncertainty where uncertainty provides an option value to waiting such that it reduces the response of a firm to a change in its fundamentals (Dixit and Pindyck, 1994; Bloom, 2009). Here, we explicitly account for the aggregate/sectoral structure of uncertainty and examine how firms use their information optimally to adjust their R&D investment. In this respect sectoral uncertainty increases the response of a firm to a sectoral
signal because sectoral uncertainty determines the precision of prior sector-level information which, in turn, affects how R&D firms respond to observed signals on the profitability of investment.\textsuperscript{5}

Our model is based on the simple idea that within a sector firms operate with a prior on the sector-level technology standard, which they update in response to a publicly observed sector-level signal each period. The sector-level signal is a sum of an aggregate economy wide component and a sector technology component, but firms do not observe these separately. When sector-level uncertainty about payoffs is high, as was the case during the Great Depression, firms have an imprecise prior concerning the path of technological development within their sector and consequently they react stronger (i.e., adjust their research investment relatively more) to sector-level signals. We propose a new “updating component” that captures this behavior. Innovations occur, or are delayed, as firms update their information and attempt to distinguish between permanent technology changes at the sector-level and transitory effects driven by aggregate level conditions.\textsuperscript{6}

The upshot is that firms extract information about the underlying fundamentals of technology from a noisy sector-level signal and use this to update their prior on the profitability of R&D investment. If firms have imprecise priors on the sector-level technology standard the “updating component” we specify means they revise their beliefs appreciably in response to the observed sector-level signal. By contrast if firms have precise priors on the underlying technology standard there is relatively less updating in the Bayesian sense. The main implication of our model is that against a backdrop of high aggregate uncertainty, relative differences in the precision of priors at the sectoral level lead to differences in innovation across sectors.

4 The Data

Our dataset consists of all firms that responded to the NRC’s direct correspondence survey of industrial research and development laboratories in the United States for five snapshot years 1921, 1927, 1931, 1933 and 1938.\textsuperscript{7} The NRC was established in 1916 and the survey was initially administered jointly by the Engineering Foundation and the NRC’s Research Information Service division (organized in 1919), in response to requests by various governmental agencies for infor-

\textsuperscript{5}Additionally our approach shares some characteristics with Schankerman (2002) which examines the relative importance of different types of shocks (idiosyncratic firm-specific shocks versus aggregate shocks common to all firms) as a determinant of firm-level investment. At a broader level our approach combines insights from Ramey and Ramey (1995) and Imbs (2007) which find differences in the effect of volatility on growth at the aggregate and sectoral level.

\textsuperscript{6}This structure is similar to Lucas (1973) where firms within a sector observe a sector-specific price (which is the sum of an aggregate component and a sectoral component) and use that information to update their prior.

\textsuperscript{7}This data source has been used by Mowery (1981) and for various years by other researchers (e.g., MacGarvie and Furman, 2007) to track the growth of industrial research in America and the development of a scientific infrastructure for innovation. Mowery and Rosenberg (1991) summarize the NRC data showing that the interwar years were a critical growth phase in the evolution of the US R&D system. No study, however, has matched the NRC data with patent data.
mation on the location of research scientists and R&D facilities. The original letter of request sent to firms with research laboratories states that “[t]he purpose is to aid the Government and the industries in the period of reconstruction and the years following, and thus to further the welfare of our nation and of the world through the advancement of American industry, engineering and science.” The catalogue of research laboratories became a central part of the NRC’s repository of research information. Its popularity and the need for consistent data led to the follow-up surveys.\footnote{The NRC archives contain various letters of request for information on research laboratories from foreign and domestic entities. For example, an official request from the Italian Government is made in a letter of May 28th, 1919. A request of November 10th 1922 states: “Mr. Louis Domeratsky, Assistant Director of the Bureau of Foreign and Domestic Commerce, wishes as complete a list as possible of private corporations in this country which devote a proportion of their resources to research purposes.” We are very grateful to Janice Goldblum, archivist at the National Research Council in Washington D.C. for pointing us to the Research Information Service archive files.}

We constructed an unbalanced panel including every firm listed in any of the surveys. This spans the whole range of corporate R&D from large companies like AT&T, General Electric and DuPont who invested several million dollars per annum in their labs to smaller concerns such as the New England Confectionery Company who employed between one and three research workers from 1921-1938. The broad and comprehensive coverage of our dataset is distinct. Other works focus on particular industries such as the changing productivity of manufacturing plants in motor vehicles during the Great Depression (Raff and Bresnahan, 1991) or the effect of technology choice on market structure in the tire industry (Klepper and Simons, 2000). The industry-level dataset used by Bernanke and Parkinson (1991) to examine labor hoarding over the business cycle during the interwar years covers a smaller share (approximately 20 percent, or eight industries) of the manufacturing sector.

From the NRC surveys we collected total research employment numbers at the firm-level. For firms that operated more than one lab (16 percent), we summed the research employment numbers across labs. The total number of firms in our dataset is 2,777. Median research employment in the data as a whole is between 7 and 8 from 1921 to 1933 rising to 15 for the 1938 survey. Between 5 and 10 percent of the labs across the survey years employed more than 100 research workers. The largest lab in the dataset is Bell Labs, established in 1925, which listed research employment of 3,008 in 1931. The spatial location of the labs is illustrated in Figure 4, which shows the strong concentration of R&D activity in the east coast manufacturing belt.

### 4.1 Patents and Historical Citations

Next, we matched our firms up against all successful US patent applications between 1921 and 1938 using the European Patent Office’s PATSTAT database. Firm names in our sample were hand-matched against assignee names in the patent data. We found that 53 percent of our firms
The R&D firms we observe applied for over 132,000 patents, equivalent to approximately 17 percent of total patents granted by the USPTO or 41 percent of patents granted to corporations over the eighteen year time span of our study. Table 1 shows that patenting firms are 3 to 4 times larger by research employment than non-patenting firms. Figure 5 illustrates the propensity to patent across sectors (i.e., the fraction of R&D labs that patent in each sector), constructed by matching R&D activities to value added industries. It can be seen by proximity to the 45 degree line that the sectoral propensity to patent remains relatively constant between the 1920s and 1930s. This suggests that the mix between basic (unpatentable) and applied (patentable) R&D did not change across the two decades.

Our contention is that by using patents as of their application date, we are measuring early stage R&D rather than the late stage development of existing ideas. On that basis, we follow the distinction of Francois and Lloyd-Ellis (2008) between R&D, commercialization and implementation, whereby R&D generates ideas that are “patented immediately”. Hall, Griliches and Hausman (1986) find strong empirical evidence of a contemporaneous link between R&D investment and patenting. We assume that patents are filed relatively early in the multistage research process. R&D is an important determinant of technical change and patents are a well-documented measure of innovation (Griliches, 1990).

To improve on the raw patents in the PATSTAT dataset, we also collected historical citation counts for each patent using a new dataset containing references to prior art in US patents granted between 1947 and 2008. Following a change in the examination procedure, patents from February 1947 onwards contain references to prior art listed on the published patent, and not just in the administrative records or “file wrapper” held at the USPTO. Previous research (e.g., Nicholas, 2008) has used patent citations based on the NBER data, which start with patents in 1975. With the new data, we reduce the citations lag by almost three decades. Patents granted in the US between 1947 and 2008 cited the 1921-1938 patents over 435,000 times, which gives us a way of evaluating the quality of innovation. 74 percent of the patents assigned to R&D firms in our data are cited at least once, with a mean citation count for cited patents of 4.5 and a range between 1 and 190. Self citations were removed by excluding all citations where the patent assignee on the citing and cited patent matched.

Historical patent citations can be interpreted in a similar way to modern citations, which have become a standard method in the literature to adjust for patent quality (Hall, Jaffe and Trajtenberg, 2005). Cumulative citations to earlier patents tend to be lower, ceteris paribus (see

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9This is consistent with Cohen, Nelson and Walsh’s (2002) finding that patenting is one of a range of appropriability mechanisms used by late twentieth century R&D firms.

10We find an average three year delay until the grant date. Our model and empirical analysis do not address the impact of uncertainty on late stage development of existing ideas.

11The most highly cited patent is 2,027,962 a plastic compositions patent granted to Lauchlin Currie of Lakewood, Ohio and assigned to the National Carbon Company of Cleveland, Ohio.
This arises because the information contained in earlier patents gets absorbed into later patents over time. Therefore we weighted citations using the overall citation distribution by application year as described in the Data Appendix. Since the aggregate citation distribution is relatively stable this weighting method provides normalized firm-year citations for comparing patent quality over time.

4.2 Uncertainty and Signal Measures

We view uncertainty as a key explanatory variable in determining R&D investment decisions given the high volatility of the stock market during the Depression years. Schwert (1990) estimates that the standard deviation of market returns was two-to-three times higher than normal at this time with peak volatility being reached in 1932. Bloom (2009) notes that uncertainty was unusually persistent between 1929 and 1932 compared to in the aftermath of other shocks such as the Cuban missile crisis or 9/11 where uncertainty led to transitory adjustments in economic activity.

We use the standard deviation of daily stock returns from CRSP as measures of uncertainty. Equity-based measures of uncertainty are well-established in the literature on irreversible investment going back to the study of Leahy and Whited (1996). Because we have a wide distribution of firm sizes in our data and want to assess priors independently of firm size, we use mainly equal-weighted portfolio returns although we also check our results are robust to using value-weighted alternatives. Since CRSP data only start annually in 1926 we took the standard deviation of daily returns at year $t$ on the market portfolio as our measure of aggregate uncertainty and the standard deviation of daily returns at year $t$ for portfolios organized by two-digit SIC code for sector-level uncertainty. Pakes (1985) and Schankerman (2002) show that stock market returns convey important information about the returns to investment and inventive activity. We use lagged mean sector-level daily stock returns as our measure of the signal firms respond to.

When measured in the conventional way as the variability of stock prices, uncertainty has “catch-all” characteristics and our interest lies in the component related to beliefs about technology.\footnote{Political uncertainty has been identified as a main driver of volatility during the Great Depression given \textit{ex ante} expectations of capitalism’s demise (Merton, 1987). According to Voth (2005) variables measuring political risk account for as much as two thirds of stock price variability across ten countries during the interwar years.} We exploit the fact that during the 1930s sector-level uncertainty rose relative to aggregate uncertainty as indicated in Figure 3. We consider that firms alter their research investment more in response to permanent technology changes at the sector-level rather than transitory gains driven by aggregate level conditions. The signal extraction problem is more pronounced when sector-level uncertainty rises relative to aggregate uncertainty.
4.3 Moody’s Variables

We also collected accounting year firm-level variables for all R&D firms that we could trace in Moody’s Manual of Industrials. Our objective here is to control for confounding effects operating through the size of firms and through liquidity. Large firms may be more immune to uncertainty than small firms. Panel data evidence suggests that financial constraints or changes in the supply of finance can explain cycles in R&D investment (Aghion et.al., 2008; Brown, Fazzari and Petersen, 2008). In particular, in upturns when cash flow is high, credit-constrained firms may find it easier to borrow and can also devote more of their own resources to R&D. In downturns, when cash flow is low, financial market imperfections prevent firms from borrowing and their own resources also preclude investment in R&D.

The information contained in Moody’s allows us to obtain data on fixed capital (to proxy for size) and working capital (to proxy for liquidity) for 30 percent of the patenting firms in our dataset. All variables are adjusted for inflation using a GDP deflator (1929=100). Although cash-flow statements did not exist during our time period, working capital is a particularly useful measure of liquidity sensitivities because it allows firms to smooth investment over the business cycle as noted by the accounting historian Dewing (1941) and in modern studies of financing constraints (e.g., Fazzari and Petersen, 1993). Firms for which we have financials applied for more patents (average of 44 per year) than firms we don’t have financials for (average of 16 per year), reflecting that the mostly publicly traded firms surveyed by Moody’s tended to be larger than non-publicly traded firms. Mean fixed capital is $59.6 million and mean working capital $22.4 million, which implies a similar ratio of fixed to working capital to that observed in modern manufacturing firms (Fazzari and Petersen, 1993, p.332).

5 Empirics

In order to test our hypothesis that the onset of high uncertainty induced learning and updating by research firms, we study the relationship between firm-level patenting and uncertainty. The empirical specifications that we run are guided by the model set out in the Appendix. Equation (4) indicates that investment is a function of the sector-level signal $\gamma_s$, aggregate uncertainty $\sigma_z^2$, and sector-level uncertainty $\sigma_v^2$. The model predicts that the response of firms to the sector-level signal is influenced by the precision of the prior. When the prior is precise ($\sigma_v^2$ is relatively low compared to $\sigma_z^2$), firms respond less to the observed signal. Following Pakes (1985) we assume that revisions to research investment take place at the beginning of the year. The association between uncertainty and innovation implied by the model is captured in the timeline below and in the subsequent estimating equation:
The timeline indicates that firms inherit a prior at the start of year \( t - 1 \) (summarized by the sector-level indicators, mean \( \mu_s \) and standard deviation \( \sigma_v \)), which is updated based on the signal \( \gamma_s \) observed during the year, leading to the R&D investment and patent application at the start of year \( t \). The baseline specification we run is as follows:

\[
\begin{align*}
\text{patents}_{ijt} &= \beta_1 \text{signal}_{jt-1} + \beta_2 \sigma_{vjt-2} + \beta_3 (\text{signal}_{jt-1} \times \sigma_{vjt-2}) + \beta_4 \text{mean prior}_{j(t-2,t-4)} \\
&\quad + \beta_5 (\text{mean prior}_{j(t-2,t-4)} \times \sigma_{zt-2}) + \alpha_i + \gamma_t + \epsilon_{ijt}.
\end{align*}
\]

Our dependent variable \( \text{patents}_{ijt} \) is a count of patents filed by firm \( i \) operating in sector \( j \) during year \( t \), where we treat the patents observed in year \( t \) as a contemporaneous proxy for research investment following Hall, Griliches and Hausman (1986). We also run regressions controlling for the quality of patents using weighted historical citation counts as a dependent variable. The variable \( \text{signal}_{jt-1} \) is the mean of daily stock returns in sector \( j \) during the previous year, \( \sigma_{vjt-2} \) (sector-level uncertainty) is the standard deviation of sector-level daily stock returns in sector \( j \) from two years preceding the year in which the patents are filed. An additional variable suggested by the theory is the mean of daily sector returns in years \( t-2 \), \( t-3 \) and \( t-4 \) (which is a measure of the prior mean, \( \mu_s \)) and we also include the interaction of the mean prior and aggregate uncertainty. The term \( \alpha_i \) is a firm fixed effect capturing different patenting propensities across firms. We use time dummies \( \gamma_t \) in all of our specifications to control for annual shocks.

The coefficient \( \beta_3 \) on the interaction term captures the effect of the “updating component” from our theory. It measures the differential response of patenting to the sector-level signal depending on the magnitude of sector-level uncertainty.\(^{13}\) Our model predicts that firms respond to the observed signal more strongly when their prior is imprecise (i.e., \( \sigma_v \) is relatively large) and less so when their prior is precise. The specification tests this hypothesis by estimating the extent to which the departure of firms’ patenting behavior from their own individual average responds to the updating component. Our starting year is 1930 because we are interested in shifts in patenting during the Depression era. Firms inherit their priors from before the Great Crash of 1929 and

\(^{13}\)This relationship between the response of firms and the variance of the sector-specific component of the signal that firms respond to also emerges in Lucas (1973).
update their expectations based on the observed signals. We estimate the specification for the period 1930-1936 as a whole, and for two key sub-intervals: the downturn during 1930-32, and the recovery phase from 1933-36. We drop 1937 and 1938 to avoid confounding our results with the recession from May 1937 to June 1938 and the build-up to the impending military conflict.\textsuperscript{14} Our periodization coincides with two major swings in the 1930s business cycle.

6 Results

6.1 Main specifications

Our main specification results are reported in Table 3. Because patents and citations are non-negative integers we estimate the model using count data regressions. We use the Poisson Quasi Maximum Likelihood (PQML) fixed effects estimator described in Wooldridge (1999) which produces consistent estimates of the parameters under very general assumptions about the conditional mean of the dependent variable. The PQML estimator is robust to heteroskedasticity and any arbitrary pattern of within-firm serial correlation.\textsuperscript{15} We cluster our standard errors at the firm-level, thereby eliminating potential concerns that we may be overstating the extent of variation in the data. Consequently, this makes it harder to detect significant effects since the standard errors are always larger on our updating component when compared to clustering by sector.

Columns 1 to 3 of Table 3 use firm year patent counts as the dependent variable and columns 4 to 12 use weighted citation counts derived from citations in 1947 to 2008 US patents. If uncertainty affected innovation in the way specified by our theory we would expect to find a strong positive effect of the updating component on patenting activity (i.e., the variable Sec.Return\textsubscript{j,t\textminus1} x Sec.Uncertainty\textsubscript{j,t\textminus2}). Where firms have imprecise priors on the sector-level technology standard they attach more importance to the sectoral signal to guide their beliefs about the expected payoff to innovation.

In column 1 we find that the updating component is statistically insignificant for the 1930-36 time period, but it is positive and statistically significant for the period 1930-32. When evaluated at the 1930-32 mean daily sector return (−0.05) and shifting from the 10th percentile (1.13) to the 90th percentile (3.08) of the sectoral uncertainty distribution, the updating coefficient implies a 5.5 percent reduction in patent counts. Firms exposed to the highest levels of sectoral uncertainty experienced a larger absolute decline in patenting in response to the negative returns during this period than firms experiencing much lower uncertainty.\textsuperscript{16} In column 3 the updating coefficient is

\textsuperscript{14}Our empirics cannot be estimated for the 1920s due to the requirement of stock market variables dated up to time \(t−4\). CRSP starts only in 1926.

\textsuperscript{15}It is implemented using the procedure of Simcoe (2007).

\textsuperscript{16}The p-value from the Wald test of significance on the coefficients for the main plus the interactive effect is
smaller in size and is not statistically significant, suggesting the effects of learning and updating on early stage R&D were concentrated in the early years of the Depression.

In columns 4 to 6 we replicate the specifications using all citation-weighted counts as the dependent variable. We find that the baseline effect for the 1930-36 period and the 1933-36 sub-period is statistically insignificant and in column 5 we confirm the result reported in column 2 for the sub-period 1930-32.\textsuperscript{17} At the mean daily sector return the estimate of the updating component equates to a 9.4 percent reduction in citation counts going from the 10th percentile to the 90th percentile of the sector-level uncertainty distribution.\textsuperscript{18}

In the remaining columns we look at the effect of the updating component when running the regressions at different points of the citations distribution. To the extent that firms can distinguish between potentially high quality innovations and those that are not likely to be influential, the learning and updating mechanism we specify is likely to be more relevant when it comes to patents that are attached to innovations that turn out to be of a high quality.

In columns 8 and 11 for the 1930-32 sub-period the updating component is economically large and highly statistically significant, whereas for the 1933-36 recovery period the updating component is economically small and statistically insignificant. Figure 7 provides a graphical representation of the effect by plotting the change in citation-weighted patents, evaluated at the mean sector return. Using firms in the lower percentile of the uncertainty distribution as a comparison group shows that the effects of updating are quantitatively important. Moving from the the 10th per-

\textsuperscript{0.072. The total derivative of patenting with respect to sector-level returns is}

\[
\frac{dpatent}{dsignal} = -2.487 + 1.105\sigma_v,
\]

which turns positive for \(\sigma_v > 2.25\%\). 33 percent of our observations are above this threshold value. The total derivative suggests that the correlation between the sector signal and firm-level patents is negative for low levels of sector uncertainty, but turns positive beyond the calculated threshold. Our theory accommodates both effects. When faced with negative stock returns, firms reduce their flow research investment, but at low levels of sector uncertainty, the investment continues to be positive and therefore the stock of research capital continues to be augmented. As long as the stock of research capital is augmented, the expected number of successful innovations (i.e. the number of patents applied for) increases as well. Alternatively, beyond the threshold level of sector uncertainty, not only are firms reducing the rate of investment but this rate turns negative and the research capital stock declines. Associated with this downsizing of research capital, the expected number of patents declines as well.

\textsuperscript{17}The total effect of sector returns on patenting in column 5 is again significantly different from zero (the p-value from the Wald test of significance on the coefficients for the main plus the interactive effect is 0.029), and turns positive for values of sectoral uncertainty greater than 2.14 percent. The total derivative of patenting with respect to sector-level returns is

\[
\frac{dpatent}{dsignal} = -3.540 + 1.720\sigma_v,
\]

which turns positive for \(\sigma_v > 2.05\%\). 42 percent of our observations are above this threshold value.\textsuperscript{18} In order to compare the coefficients across specifications in columns 2 (patents) and 5 (citations) more effectively we also re-ran the regressions on normalized patent and citation variables. The respective coefficients of 0.78 (s.e. 0.32) and 0.99 (s.e. 0.46) on the signal \(\times\) uncertainty interaction show that the learning and updating effects in the case of citations are larger in magnitude than in the case of raw patents. Full results available on request.
centile to the 90th percentile of the sector-level uncertainty distribution, citation-weighted patents are 23 percent lower at the 75th percentile cut-off and 32 percent lower based on the estimate in column 11 for above 90th percentile citations.

6.2 Robustness Checks

In Tables 4A and 4B we provide robustness checks on the citation-weighted coefficients for the 1930-32 and 1933-36 sub-periods contained in Table 3. In the first three columns we use value-weighted measures in the construction of both return and uncertainty variables on the right hand-side of equation 4. Although the coefficient in column 1 is statistically insignificant, and smaller compared to the coefficient using equal-weighted returns (column 5 of Table 3) the coefficients at the 75 percentile cut-off are similar in size. When above 90th percentile citations are used as the dependent variable (column 3), the updating component is significant at better than the 5 percent level and it is also of a similar economic magnitude to the corresponding coefficient using equal-weighted measures in column 11 of Table 3. For the 1933-36 recovery period none of the updating component coefficients using value-weighted measures is statistically significant.

Reverting to equal-weighted measures, and our 75th percentile citation cut-off point, columns 4 to 7 of Tables 4A and 4B check the updating component is robust to different types of firms in the data. Weak performing firms, for example, may exit causing a systematic measurement error when parameterizing the effect of uncertainty on research investment. Although we do not observe entry and exit directly (e.g., firms may be missing from the NRC volumes for a particular year because they failed to respond to the survey) in columns 4 and 5 we run our specification both including and excluding balanced panel firms we observe in every year of the NRC surveys. Our results indicate a smaller updating response for balanced panel firms, suggesting larger surviving firms revised their beliefs relatively less in response to the observed sector-level signal.

Differences in the size of the updating term can also be seen when running the regressions including and excluding firms we observe in Moody’s Manual of Industrials (columns 6 and 7). This is another proxy for size and survivors since mostly publicly traded firms reported their balance sheets. The most important result, however, is that the updating component is significant at the customary levels in all the specifications in columns 4 to 7 regardless of the different types of firms considered. Furthermore, consistent with our other results, the updating component is statistically insignificant in all specifications for the sub-period 1933-36 (Table 4B).

6.3 Firm-Level Controls

In Table 5 we exploit our firm financial data further by adding firm level controls to our main specification maintaining equal-weighted signal and uncertainty measures, and our 75th percentile
citation cut-off point. Bigger and more financially liquid firms may be able to smooth out their investments in innovation over the business cycle despite facing uncertainty concerning payoffs to early stage R&D. We report estimates of the updating component using firm-level controls for size (plant and equipment) and liquidity (working capital) based on our data match with balance sheets and income statements in Moody’s. Due to the limited availability of financial data and the coverage of larger publicly-traded firms in Moody’s, the sample size is reduced. We include firm-level controls linearly and as interactions to test whether these observables drive the updating term.

In the first column of Table 5, even with the fixed capital interaction term being statistically significant the updating component still enters in a way suggested by our theory and with an economic magnitude very similar to the corresponding estimate in column 8 of Table 3. Noticeably, the liquidity variable also enters positively and significantly in interaction form, in column 2 suggesting that firms facing weaker credit constraints were more able to innovate in the face of uncertainty (Aghion et al., 2005, 2008). Yet despite finding size and liquidity sensitivities, the updating component we estimate is still almost exactly the same size as the baseline estimate in column 8 of Table 3. Moreover, in column 3 of Table 5, while the updating component is robust when adding both firm fixed assets and liquidity variables in, the firm-level controls themselves are not statistically significant.

In columns 4 to 6 of Table 5, we examine the upturn of the business cycle during 1933-36 and show again that the updating component is statistically insignificant. Overall our analysis of the specifications with firm-level controls is consistent with the rest of our results, namely that the main effect of learning and updating took place as firms adjusted to the extreme adverse shock and the initial onset of high uncertainty after the Great Crash.

6.4 Specific Sectors

Finally, Tables 6A and 6B estimate the main specification for specific sectors. In the first two columns we partition our sample into high and low uncertainty sectors based on industries with above and below median sector-level uncertainty. Recall that our model specifies that sectors in which firms have tight prior distributions on the payoff to innovation are likely to experience less of a change in R&D in response to the observed signal compared to sectors in which firms operate with diffuse, or high variance, prior distributions on payoffs. Therefore, the effect of the updating component should be more pronounced in high uncertainty sectors. Reassuringly, the estimate on the updating component in column 1 for high uncertainty sectors is economically and statistically significant, but not in the low uncertainty sectors in column 2. Neither high nor low uncertainty sector coefficients are statistically significant between 1933-36 (Table 6B columns 1 and 2).

Even more encouraging are the estimates in columns 3 and 4 which split the data into sectors...
according to their orientation towards consumer durables. Because of uncertainty, purchases of consumer goods like sewing machines and refrigerators fell off sharply from the last quarter of 1929, which plausibly affected irreversible investment on the producer side. As Romer (1990, p.603) points out: “if producers become temporarily uncertain about future income, then it may be optimal for them to postpone purchases of new plant and equipment until they learn more about the future health of the economy”. Our estimates indicate clear knock-on effects since the coefficients measuring learning and updating are much larger and more precisely estimated in consumer durables sectors relative to non-consumer durables sectors. Figure 8 illustrates the effect graphically. At the mean daily sector return for consumer durables, the estimate in column 3 of Table 6A equates to a 45 percent reduction in citation counts going from the 10th percentile to the 90th percentile of the consumer durables uncertainty distribution.

The results also suggest economically important effects of uncertainty on innovation in intermediate good relative to final good sectors given the coefficient on the updating term is large and statistically significant in column 5 of Table 6A and insignificant in column 6. In the Schumpeterian growth model (Aghion and Howitt, 1992) new ideas in intermediate good sectors are assumed to instantaneously translate into new patents whereas in our extension of this model improved intermediate good innovations may be delayed if firms in these sectors have imprecise priors and receive negative signals on the payoffs to early stage R&D. Figure 8 illustrates that at the mean daily sector return for intermediate good sectors, the estimate in column 5 of Table 6A translates into a 28 percent reduction in citation counts going from the 10th percentile to the 90th percentile of the uncertainty distribution. The coefficients for both consumer durables and intermediate good sectors remain positive and statistically significant in Table 6B for the 1933-36 sub-period. However, the economic magnitude of the estimates is much smaller than the corresponding estimates of the updating component between 1930 and 1932 (Table 6A).

7 Conclusion

According to Bernanke (1986), the Great Depression provides a unique set of events that can advance our understanding of macroeconomic disruptions. In this paper, we have attempted to shed light on interactions between two key variables - uncertainty and innovation - using new theory and new data on the US corporate R&D sector. While several authors have pointed to the high levels of uncertainty as a defining characteristic of the Depression years (Merton, 1987; Schwert, 1989; Romer, 1990; Bloom, 2009) there is no evidence on the link between uncertainty and firm-level behavior at this time. Understanding the mechanisms driving the rate and direction of innovation has long been an important issue in the economics of technological change (Schmookler, 1966). Our model of innovation under uncertainty is motivated by the historical record showing that
some innovations advanced during the 1930s while other innovations were delayed. In our setup such differences arise when firms face a signal extraction problem in forming their expectations about the payoffs to early stage R&D.

Our empirical analysis shows that research investment behavior changed over the life cycle of the Great Depression. Learning and updating effects were important between 1930 and 1932 but much less so in the recovery phase from 1933 to 1936. Access to liquidity did not eliminate the consequences of persistent uncertainty suggesting even financially unconstrained firms may have been prevented from innovating countercyclically. We find the largest economic effects to be in high uncertainty, consumer durable and intermediate good sectors where firms had diffuse, or high variance, prior distributions on payoffs to early stage R&D and significantly lowered their research investment as a consequence of negative return signals. By influencing expected payoffs, the initial uncertainty shock of the Great Depression significantly changed the speed of sector-level innovation and the timing of early stage R&D.
Appendix. A Model of Innovation Under Uncertainty

A.1 Preliminaries

Consider a small, open economy with multiple sectors. Within each sector, output is produced by a firm which holds the monopoly licence/patent to the latest vintage of technology for producing the good. Also within each sector, risk-neutral potential entrepreneurs invest in research projects to develop a newer vintage of the intermediate good and displace the current incumbent.\(^{19}\)

We assume that when an innovation occurs, it is immediately adopted in production. For simplicity, we also assume that during the first time period after the successful innovation, there is an imitation technology that allows a competitive fringe sector to manufacture the intermediate good, but at a higher marginal cost of production than the innovator. After the first time period, the competitive fringe is assumed to be able to exploit the new information learned from the innovator’s patent application and re-engineer the production technique perfectly, thereby eliminating the innovator’s cost advantage. The duration of monopoly profit is therefore limited to only one time period after the innovation is made.\(^{20}\)

The monopoly profit flow in sector \(s\) at time \(t\) is given by \(\pi_{st} = \gamma_{st} R_s\), where \(R_s\) is a sector-specific constant and \(\gamma_{st}\) is a stochastic component which varies in a manner to be specified below.

A.2 The Technology Process

The stochastic component of monopoly profits is a function of two terms, the sector-level technology breakthrough \(\Psi_{st}\) and an idiosyncratic term \(z_{st}\) that represents a mix of factors determined at the level of the aggregate economy, but which varies by sector to capture the fact that sectors are affected differentially by developments at the aggregate level:

\[
\gamma_{st} = \Psi_{st} + z_{st},
\]

where \(z \sim N(0, \sigma_z^2)\) averages out to zero in the cross-section.

The sector-level technology parameter \(\Psi_{st}\) represents the true increment to knowledge at the level of the sector, whereas \(z_{st}\) reflects a transitory component that captures all factors that affect the manner in which an innovation augments profits within the sector, including business cycle conditions and spillovers from shifts in customer preferences that originate in other sectors.

Individual research firms within a sector observe the signal \(\gamma_{st}\) at the end of period \(t\), but not the separate components. In other words, firms have limited information about the aggregate economy and the specific nature of the spillovers from other sectors; furthermore, immediately after an innovation occurs, they cannot assess its true impact in terms of its increment to knowledge and the influence it will have on future research. This structure is consistent with observations on the historical record of past breakthroughs where the true impact of a new technology is often recognized only with a lag and possibly only after it generates a sequence of secondary innovations (e.g., David, 1990; Jovanovic and Rousseau, 2005).

\(^{19}\)Each research project can be thought of as a separate entrepreneurial R&D firm.

\(^{20}\)This timing assumption is made for tractability and does not qualitatively affect the analysis.
A.3 Updating

Research firms use all available information on profitability shocks in the most efficient way possible when forming their expectation of future returns to research investment. Within a sector, research firms are symmetric and, at the start of period $t$, share a common prior on the distribution of the sector-level technology shock

$$\Psi_{st} \sim N(\mu_s, \sigma^2_v).$$

Following the observation of $\gamma_{st}$, research firms update their belief about the underlying technology standard according to:

$$E(\Psi_{st} | \gamma_{st}) = \frac{\sigma^2_z}{\sigma^2_z + \sigma^2_v} \mu_s + \frac{\sigma^2_v}{\sigma^2_z + \sigma^2_v} \gamma_{st}.$$ 

The posterior variance is given by

$$Var(\Psi_{st} | \gamma_{st}) = \frac{\sigma^2_z \sigma^2_v}{\sigma^2_z + \sigma^2_v}.$$ 

The posterior mean $E(\Psi_{st} | \gamma_{st})$ is used as the estimate of $E(\gamma_{st+1})$. It is a convex combination of the prior mean, $\mu_s$, and the observed sector-level signal, $\gamma_{st}$. The weights on the two terms indicate that if the prior variance of the sector-level technology standard $\sigma^2_v$ is low relative to the variance of the aggregate shock $\sigma^2_z$, firms attach more importance to their prior and do not revise their beliefs appreciably in response to the observed increment $\gamma_{st}$. In this case, any observed deviation in signal from the prior will largely be attributed to the economy-wide transitory influences and the posterior calculation will not be influenced significantly by the observed deviation. On the other hand, when $\sigma^2_v$ is high relative to $\sigma^2_z$ (i.e., when sector-level uncertainty is high relative to aggregate uncertainty), firms do not have a precise prior on the sector-level technology standard and so they revise their priors appreciably in response to the observed signal.\(^{21}\)

The important element in the posterior mean is the updating component, $\frac{\sigma^2_z}{\sigma^2_z + \sigma^2_v} \gamma_{st}$. The updating component reflects the adjustment in expectations when firms use available information optimally. As we describe below, the updating component influences the research investment decisions of firms and the innovations that occur as a result.

A.4 Research Investment

Following their observing the signal $\gamma_{st}$, the risk-neutral research firms update their expectations to $E(\gamma_{st+1})$ as described above. Based on the revised expectations, they choose an optimal amount of investment $n_{st}$ in research capital at a cost $\frac{k}{2} n^2_{st}$ to influence the probability of successful innovation in period $t + 1$. Specifically, this investment increases the probability of success by an amount $\lambda n_{st}$. The parameters satisfy $k > 0$ and $\lambda > 0$. There are no spillovers between research firms.

From the perspective of the end of period $t$, the expected net return on investment is given

\(^{21}\)As in Lucas (1973), here too firms respond more strongly to the observed sector-level information when the variation in the sectoral component is large relative to the variation in the aggregate component. The difference is that in Lucas (1973), firms within a sector have a prior on the aggregate price which they update after they observe the sectoral price. Here, firms have a prior on the sector-level technology standard, which they update after they observe a sectoral return which is the sum of the sector-level technology standard and an aggregate component.
by
\[ V(n_{st}) = \left[ \frac{\lambda n_{st} E(\gamma_{st+1}) R_s}{1 + r} - \frac{k}{2} n_{st}^2 \right], \]

where \( r \) is the risk-free interest rate. The optimal \( n_{st} \) satisfies the following first-order condition:
\[ V'(n_{st}) = \left[ \frac{\lambda E(\gamma_{st+1}) R_s}{1 + r} - kn_{st} \right] = 0, \]

from where the investment choice follows as
\[ n_{st} = \frac{\lambda}{k} \left( \frac{E(\gamma_{st+1}) R_s}{1 + r} \right). \] (2)

The optimal research investment is an increasing function of \( E(\gamma_{st+1}) \). As described in Section A.3, this expectation is formed based on the observed sequence of signals, with
\[ E(\gamma_{st+1}) = E(\Psi_{st} | \gamma_{st}) = \frac{\sigma_z^2}{\sigma_z^2 + \sigma_v^2} \mu_s + \frac{\sigma_v^2}{\sigma_z^2 + \sigma_v^2} \gamma_{st}. \] (3)

Substituting for \( E(\gamma_{st+1}) \) in Equation (2), the optimal research investment is given by:
\[ n_{st} = \frac{\lambda R_s}{k (1 + r)} \left( \frac{\sigma_z^2}{\sigma_z^2 + \sigma_v^2} \mu_s + \frac{\sigma_v^2}{\sigma_z^2 + \sigma_v^2} \gamma_{st} \right), \] (4)

where \( n_{st} \) is the amount of research investment made after the signal \( \gamma_{st} \) is observed.

Firms’ investment decisions (and therefore the probability of a successful innovation) are affected by their expected payoff from a successful innovation. As firms revise upwards their belief about their expected payoff from a successful innovation, they increase their investment in research. This raises the probability of a successful innovation.

The key term in Equation (4) from the point of view of the empirics is the updating component, \( \frac{\sigma_v^2}{\sigma_z^2 + \sigma_v^2} \gamma_{st} \), which influences the investment decision \( n_{st} \) and the probability of successful innovation (which we observe in the data as a patent application) in period \( t + 1 \).

### A.5 Timing of Events

At the start of each time period \( t \), within each sector firms have a common prior on the underlying technology standard \( \Psi_s \sim N(\mu_s, \sigma_s^2) \). They update this prior based on the signal \( \gamma_{st} \) they observe during the period. The updating influences their investment decision \( n_{st} \), which in turn affects the probability of successful innovation in the subsequent period \( t + 1 \). If at least one of the research firms is successful in innovating, the firm acquires the monopoly rights over the sale of its

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\(^{22}\)In the interests of tractability this expression only focuses on the additional benefit to the research firm from making the innovation more likely in period \( t+1 \). The investment decision alters the entire future stream of benefits from \( t+2 \) onwards as well. The expression therefore understates the responsiveness of investment to the observed signal.

\(^{23}\)The small open economy assumption pins down the interest rate \( r \).
innovation which is immediately adopted in production in \( t + 1 \).\(^{24}\) After firms observe the profit flow \( \gamma_{st+1}R_s \) they update their beliefs and choose their optimal research investment \( n_{st+1} \).

### A.6 Uncertainty and its Effect on Research Investment

As shown above, firms revise their beliefs regarding the expected payoff to investment depending on the values of aggregate uncertainty and the sector-level uncertainty. As Equation 3 indicates, when sector-level uncertainty \( \sigma^2_s \) is high relative to aggregate uncertainty \( \sigma^2_z \) (i.e. research firms within a sector have a relatively imprecise prior on the sector-level technology standard \( \Psi_s \)), research investment decisions are more sensitive to the observed sector-level signal \( \gamma_{st} \). On the other hand, when \( \sigma^2_z \) is high relative to \( \sigma^2_v \), research investment is less sensitive to the observed signal.

\(^{24}\)In principle, it is possible that more than one firm can innovate in a given time interval. The probability of this occurring is an order of magnitude smaller than the probability of at most one innovation occurring.
B Data Appendix

B.1 National Research Council Data

We obtained data on research firms from the 1921, 1927, 1931, 1933 and 1938 editions of the National Research Council’s (NRC) *Research Laboratories in Industrial Establishments of the United States*. From each edition we collected firm-level observations including the location of the firm’s laboratory (or laboratories) and the number of research workers employed at each lab. For firms with multiple labs, we summed the number of research workers employed. Our dataset includes 2,777 firms.

B.2 Patents and Citations

We hand matched each firm in the NRC editions against patent assignees in the European Patent Office’s PATSTAT database of successful US patent applications for the period 1921-1938. We determined a patent count for each firm-year observation. 52 percent of our dataset of 2,777 firms patented at least once.

We also established firm-year citation count observations using a dataset containing all citations to US patents by US patents granted from February 1947 to September 2008. We first removed self citations. We standardized the names of patent assignees in the European Patent Office’s PATSTAT database and excluded all observations where the cited patent assignee and citing patent assignee matched. To adjust for the increase in citations (CITATIONS) to later patents because of the citations lag between when we observe successful patent applications and the first citations being made in 1947 we use a weighting factor $\omega$ for patents applied for in cohort $c$ (i.e., 1921...1938). This is calculated as the ratio of total 1947-2008 citations to patents applied for in a base year (1920) to total 1947-2008 citations for patents in cohort $c$. This method gives a smaller weight to citations in later cohorts.

$$\omega_c = \frac{\sum_{t=1947}^{2008} CITATIONS_{t}^{1920}}{\sum_{t=1947}^{2008} CITATIONS_{t}^{c}}$$

$$WCITATIONS_{ic} = \sum_{t=1947}^{2008} (CITATIONS_{ic}) \omega_c$$

Weighted citations (WCITATIONS) to the patents of firm $i$ in cohort $c$ were then defined as the absolute value of citations multiplied by the weighting factor, where absolute values were used to preserve the count property of the citations data.

B.3 Signal and Uncertainty Measures

We used CRSP daily data to construct signal and uncertainty measures used in our empirical analysis. We mapped the two-digit SIC codes (the CRSP variable “hsicmg”) into our 16 sectors listed above by restricting the CRSP datafile to manufacturing SIC codes (20 to 39) and by excluding SIC codes 33, 34, 35 and 37 to obtain a one-to-one match. The measures we use in our regressions were constructed as follows:
1. Sector Return_{j,t-1} (signal): Mean daily return inclusive of dividends at time \( t - 1 \) on an equal-weighted portfolio of firms in sector \( j \).

2. Sector Uncertainty_{j,t-2} (uncertainty): Standard deviation of the mean daily return inclusive of dividends at time \( t - 2 \) on an equal-weighted portfolio of firms in sector \( j \).

3. Sector Return_{j,t-1} \times \text{Sector Uncertainty}_{j,t-2} (updating component): interaction of 1. and 2.

4. Sector Return_{j,(t-2,t-4)} (mean prior): Mean daily return inclusive of dividends from time \( t - 2 \) to \( t - 4 \) on an equal-weighted portfolio of firms in sector \( j \).

5. Aggregate Uncertainty_{t-2}: Standard deviation of the equal-weighted market return inclusive of dividends at time \( t - 2 \).

6. Sector Return_{j,(t-2,t-4)} \times \text{Aggregate Uncertainty}_{t-2}: interaction of 4. and 5.

B.4 Sectors

Based on the description of research activities listed in the NRC reports we allocated each firm into one of 15 Census of Manufactures value added sectors and an additional miscellaneous sector. Although the Census of Manufactures reports 19 sectors for our time period we dropped four - primary metal, fabricated metal, non-electrical machinery and transportation equipment - because value added data for these categories only started in 1937. Our 16 sectors are as follows:

<table>
<thead>
<tr>
<th>Sector Category</th>
<th>Sector Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food and Kindred(^4)</td>
<td>Tobacco</td>
</tr>
<tr>
<td>Tobacco</td>
<td>Lumber &amp; Wood(^1)</td>
</tr>
<tr>
<td>Textile Mill Products(^3)</td>
<td>Furniture &amp; Fixtures(^{1,2,3})</td>
</tr>
<tr>
<td>Apparel &amp; Textiles(^1,4)</td>
<td>Paper &amp; Products(^1,3)</td>
</tr>
<tr>
<td>Paper &amp; Products(^1,4)</td>
<td>Printing &amp; Publishing(^1,4)</td>
</tr>
<tr>
<td>Printing &amp; Publishing(^1,4)</td>
<td>Chemicals(^3)</td>
</tr>
<tr>
<td>Chemicals(^3)</td>
<td>Petroleum &amp; Coal</td>
</tr>
<tr>
<td>Petroleum &amp; Coal</td>
<td>Stone, Clay &amp; Glass</td>
</tr>
<tr>
<td>Stone, Clay &amp; Glass</td>
<td>Electrical Equipment(^2,4)</td>
</tr>
<tr>
<td>Electrical Equipment(^2,4)</td>
<td>Instruments &amp; Related(^2,4)</td>
</tr>
<tr>
<td>Instruments &amp; Related(^2,4)</td>
<td>Miscellaneous(^1)</td>
</tr>
</tbody>
</table>

For our sector-level analysis we use the following categories:

\(^1\)Denotes high uncertainty sectors (i.e., above 50th percentile uncertainty based on the standard deviation of sector-level returns).

\(^2\)Denotes consumer durables sectors

\(^3\)Denotes intermediate good sectors

\(^4\)Denotes final good sectors

B.5 Financial Variables

We matched each firm in the NRC volumes against balance sheet and income statement data reported in Moody’s Manual of Industrials. Where available, we extracted the following items: fixed capital, working capital and sales. We obtained at least one of these variables for 30 percent of the patenting firms in our dataset. All of our variables were converted to real values using a GDP deflator (1929=100) calculated using the data in Johnston and Williamson (2008).
References


Johnston, Louis and Samuel H. Williamson., “The Annual Real and Nominal GDP for the United States, 1789 - Present,” Available at Economic History Services, 2008,


Table 1. Employment of Research Workers for Patenting and non-Patenting Firms

<table>
<thead>
<tr>
<th></th>
<th>Non-Patenting Firms</th>
<th>Patenting Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Research Workers, 1921</td>
<td>6.17 (7.10)</td>
<td>24.45 (113.78)</td>
</tr>
<tr>
<td></td>
<td>[194]</td>
<td>[292]</td>
</tr>
<tr>
<td>Research Workers, 1927</td>
<td>7.64 (9.38)</td>
<td>23.92 (102.92)</td>
</tr>
<tr>
<td></td>
<td>[402]</td>
<td>[559]</td>
</tr>
<tr>
<td>Research Workers, 1931</td>
<td>8.39 (13.27)</td>
<td>25.59 (123.22)</td>
</tr>
<tr>
<td></td>
<td>[643]</td>
<td>[940]</td>
</tr>
<tr>
<td>Research Workers, 1933</td>
<td>7.42 (9.84)</td>
<td>22.78 (96.82)</td>
</tr>
<tr>
<td></td>
<td>[613]</td>
<td>[917]</td>
</tr>
<tr>
<td>Research Workers, 1938</td>
<td>16.35 (25.52)</td>
<td>46.59 (152.97)</td>
</tr>
<tr>
<td></td>
<td>[714]</td>
<td>[1036]</td>
</tr>
</tbody>
</table>

Notes: Research worker employment numbers are from the NRC surveys and are reported as means with standard deviations in parentheses. Number of firms used for constructing the mean is in squared brackets. Patenting firms are defined as those in the NRC volumes that we matched up with patent assignee names in the European Patent Office’s PATSTAT database of successful patent applications between 1921 and 1938. Non-patenting firms are defined as those in the NRC volumes for which no matching patent assignee could be found.

Table 2. Annualized Research Worker Employment Growth Rates for Patenting Firms

<table>
<thead>
<tr>
<th></th>
<th>Annual Growth Rate of Research Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Firms</td>
</tr>
<tr>
<td>1921 to 1927</td>
<td>0.04 (0.10)</td>
</tr>
<tr>
<td>1927 to 1931</td>
<td>0.07 (0.18)</td>
</tr>
<tr>
<td>1931 to 1933</td>
<td>-0.03 (0.25)</td>
</tr>
<tr>
<td>1933 to 1938</td>
<td>0.18 (0.20)</td>
</tr>
<tr>
<td>1921 to 1938</td>
<td>0.07 (0.08)</td>
</tr>
</tbody>
</table>

Notes: Research worker employment numbers are from the NRC surveys and are reported as annualized average firm-level growth rates between the specified survey years with standard deviations in parentheses. We observe research worker employment figures for 142 patenting firms consistently across all of the survey years between 1921 and 1938. These data points are used for calculating the annualized firm-level growth rates reported in the column “Firms Observed Every Year”.
Table 3. Poisson QML Regressions for the Effect of the Updating Component on Patents and Citation-Weighted Patents

<table>
<thead>
<tr>
<th></th>
<th>Patents 1930-36</th>
<th>Patents 1930-32</th>
<th>Patents 1933-36</th>
<th>Citation-Weighted Patents All Citations 1930-36</th>
<th>Citation-Weighted Patents &gt;75th Percentile Citations 1930-36</th>
<th>Citation-Weighted Patents &gt;90th Percentile Citations 1930-36</th>
<th>Citation-Weighted Patents &gt;75th Percentile Citations 1930-32</th>
<th>Citation-Weighted Patents &gt;90th Percentile Citations 1930-32</th>
<th>Citation-Weighted Patents &gt;75th Percentile Citations 1933-36</th>
<th>Citation-Weighted Patents &gt;90th Percentile Citations 1933-36</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector Return (j,t-1)</td>
<td>-0.466</td>
<td>-2.487</td>
<td>-0.060</td>
<td>0.094</td>
<td>-3.540</td>
<td>-0.210</td>
<td>0.371</td>
<td>-5.200</td>
<td>-0.871</td>
<td>0.415</td>
</tr>
<tr>
<td></td>
<td>[0.313]</td>
<td>[1.317]c</td>
<td>[0.342]</td>
<td>[0.342]</td>
<td>[1.516]b</td>
<td>[0.417]</td>
<td>[0.473]</td>
<td>[2.068]b</td>
<td>[0.625]</td>
<td>[0.615]</td>
</tr>
<tr>
<td>Sector Uncertainty (j,t-2)</td>
<td>-0.053</td>
<td>0.033</td>
<td>-0.075</td>
<td>0.039</td>
<td>0.069</td>
<td>-0.124</td>
<td>-0.046</td>
<td>0.133</td>
<td>-0.260</td>
<td>-0.072</td>
</tr>
<tr>
<td></td>
<td>[0.040]</td>
<td>[0.066]</td>
<td>[0.056]</td>
<td>[0.056]</td>
<td>[0.086]</td>
<td>[0.075]</td>
<td>[0.081]</td>
<td>[0.137]</td>
<td>[0.115]b</td>
<td>[0.102]</td>
</tr>
<tr>
<td>Sec. Return (j,t-1) x Sec. Uncertainty (j,t-2)</td>
<td>0.076</td>
<td>1.105</td>
<td>0.118</td>
<td>-0.022</td>
<td>1.720</td>
<td>0.119</td>
<td>-0.065</td>
<td>2.544</td>
<td>0.267</td>
<td>-0.011</td>
</tr>
<tr>
<td></td>
<td>[0.073]</td>
<td>[0.618]c</td>
<td>[0.081]</td>
<td>[0.093]</td>
<td>[0.745]b</td>
<td>[0.107]</td>
<td>[0.133]</td>
<td>[0.980]a</td>
<td>[0.167]</td>
<td>[0.175]</td>
</tr>
<tr>
<td>Firms</td>
<td>598</td>
<td>440</td>
<td>504</td>
<td>598</td>
<td>440</td>
<td>504</td>
<td>540</td>
<td>389</td>
<td>445</td>
<td>435</td>
</tr>
<tr>
<td>Sectors</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is an annual count of patents or citation-weighted patents for firm \(i\) in sector \(j\) at time \(t\). A Poisson Quasi Maximum Likelihood firm fixed effects estimator is used. All specifications include the following additional variables, which are described in more detail in the data appendix: Sector Return \(j,t-1\) and the interaction of this variable with Aggregate Uncertainty \(j,t-2\). The number of firms/observations varies for patent and citation-weighted patent specifications according to the number of firms for which a “within” series of data are available. Robust standard errors clustered by firm are reported in parentheses: “a” is for significance at the 1 percent level “b” for the 5 percent level and “c” for the 10 percent level.
Table 4A. Robustness Checks: Citation-Weighted Patents, 1930-32

<table>
<thead>
<tr>
<th>Value Weighted Measures</th>
<th>&gt;75th Percentile Citations</th>
<th>&gt;90th Percentile Citations</th>
<th>Balanced Panel Firms</th>
<th>Excluding Balanced Panel Firms</th>
<th>Firms with Financials</th>
<th>Excluding Firms with Financials</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Citations</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sector Return_{j,t-1}</td>
<td>-0.793</td>
<td>-2.785</td>
<td>-6.324</td>
<td>-4.868</td>
<td>-7.241</td>
<td>-5.083</td>
</tr>
<tr>
<td></td>
<td>[1.277]</td>
<td>[2.473]</td>
<td>[3.309]</td>
<td>[2.534]</td>
<td>[2.637]</td>
<td>[2.573]</td>
</tr>
<tr>
<td>Sector Uncertainty_{j,t-2}</td>
<td>-0.266</td>
<td>-0.214</td>
<td>-0.446</td>
<td>0.303</td>
<td>-0.102</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>[0.115]</td>
<td>[0.210]</td>
<td>[0.263]</td>
<td>[0.175]</td>
<td>[0.208]</td>
<td>[0.191]</td>
</tr>
<tr>
<td>Sec. Return_{j,t-1} x Sec. Uncertainty_{j,t-2}</td>
<td>0.681</td>
<td>2.088</td>
<td>4.417</td>
<td>2.343</td>
<td>3.675</td>
<td>2.018</td>
</tr>
<tr>
<td></td>
<td>[0.720]</td>
<td>[1.466]</td>
<td>[1.955]</td>
<td>[1.178]</td>
<td>[1.134]</td>
<td>[1.174]</td>
</tr>
<tr>
<td>Firms</td>
<td>440</td>
<td>389</td>
<td>290</td>
<td>137</td>
<td>252</td>
<td>166</td>
</tr>
<tr>
<td>Sectors</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>13</td>
<td>15</td>
<td>13</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is an annual count of citation-weighted patents for firm i in sector j at time t. A Poisson Quasi Maximum Likelihood firm fixed effects estimator is used. All specifications include the following additional variables, which are described in more detail in the data appendix: Sector Return_{j,t-1}, Sector Uncertainty_{j,t-2}, and the interaction of this variable with Aggregate Uncertainty_{j,t-2}. Robust standard errors clustered by firm are reported in parentheses: “a” is for significance at the 1 percent level “b” for the 5 percent level and “c” for the 10 percent level.

Table 4B. Robustness Checks: Citation-Weighted Patents, 1933-36

<table>
<thead>
<tr>
<th>Value Weighted Measures</th>
<th>&gt;75th Percentile Citations</th>
<th>&gt;90th Percentile Citations</th>
<th>Balanced Panel Firms</th>
<th>Excluding Balanced Panel Firms</th>
<th>Firms with Financials</th>
<th>Excluding Firms with Financials</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Citations</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sector Return_{j,t-1}</td>
<td>-0.097</td>
<td>-0.373</td>
<td>-0.493</td>
<td>-1.417</td>
<td>-0.606</td>
<td>-1.196</td>
</tr>
<tr>
<td></td>
<td>[0.510]</td>
<td>[0.779]</td>
<td>[1.113]</td>
<td>[0.818]</td>
<td>[1.086]</td>
<td>[0.811]</td>
</tr>
<tr>
<td>Sector Uncertainty_{j,t-2}</td>
<td>-0.033</td>
<td>-0.110</td>
<td>-0.130</td>
<td>-0.240</td>
<td>-0.286</td>
<td>-0.299</td>
</tr>
<tr>
<td></td>
<td>[0.071]</td>
<td>[0.101]</td>
<td>[0.149]</td>
<td>[0.160]</td>
<td>[0.167]</td>
<td>[0.150]</td>
</tr>
<tr>
<td>Sec. Return_{j,t-1} x Sec. Uncertainty_{j,t-2}</td>
<td>0.027</td>
<td>0.020</td>
<td>0.113</td>
<td>0.243</td>
<td>0.261</td>
<td>0.304</td>
</tr>
<tr>
<td></td>
<td>[0.131]</td>
<td>[0.215]</td>
<td>[0.318]</td>
<td>[0.212]</td>
<td>[0.283]</td>
<td>[0.208]</td>
</tr>
<tr>
<td>Firms</td>
<td>504</td>
<td>445</td>
<td>339</td>
<td>136</td>
<td>309</td>
<td>221</td>
</tr>
<tr>
<td>Sectors</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>13</td>
<td>16</td>
<td>13</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Table 5. Adding Firm-Level Controls for Citation-Weighted Patents for the 1930-32 and 1933-36 Sub-Periods

<table>
<thead>
<tr>
<th></th>
<th>Citation-Weighted Patents, 1930-32 &gt;75th Percentile Citations</th>
<th>Citation-Weighted Patents, 1933-36 &gt;75th Percentile Citations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector Return$_{j,t-1}$</td>
<td>-5.593            -5.666            -5.553            -1.179            -1.240            -1.277</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[2.408]b          [2.698]b          [2.948]c          [0.804]          [0.804]          [0.787]</td>
<td></td>
</tr>
<tr>
<td>Sector Uncertainty$_{j,t-2}$</td>
<td>-0.126            -0.146            -0.148            -0.311            -0.328            -0.317</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.240]           [0.237]           [0.239]           [0.166]c          [0.156]b          [0.159]b</td>
<td></td>
</tr>
<tr>
<td>Sec. Return$<em>{j,t-1}$ x Sec. Uncertainty$</em>{j,t-2}$</td>
<td>2.325             2.564             2.499            0.306             0.325             0.333</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[1.031]b          [1.106]b          [1.266]b          [0.207]          [0.208]          [0.208]</td>
<td></td>
</tr>
<tr>
<td>log (Fixed Capital)$_{i,j,t-1}$</td>
<td>-0.161            -0.028            -0.028            -0.117            -0.034            -0.034</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.255]           [0.339]           [0.126]           [0.173]</td>
<td></td>
</tr>
<tr>
<td>log (Fixed Capital)$<em>{i,j,t-1}$ x Sec. Uncertainty$</em>{j,t-2}$</td>
<td>0.090             0.013             0.004             0.026             0.026             0.026</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.034]a          [0.113]           [0.017]           [0.044]</td>
<td></td>
</tr>
<tr>
<td>log (Liquidity)$_{i,j,t-1}$</td>
<td>0.412             0.433             0.292             0.222             0.183             0.241</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.349]           [0.404]           [0.183]           [0.241]</td>
<td></td>
</tr>
<tr>
<td>log (Liquidity)$<em>{i,j,t-1}$ x Sec. Uncertainty$</em>{j,t-2}$</td>
<td>0.102             0.088             0.010             0.036             0.018             0.050</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.034]a          [0.122]           [0.018]           [0.050]</td>
<td></td>
</tr>
</tbody>
</table>

Firms | 166 | 166 | 166 | 221 | 221 | 221 |
Sectors | 13 | 13 | 13 | 13 | 13 | 13 |
Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variable is an annual count of citation-weighted patents for firm $i$ in sector $j$ at time $t$. A Poisson Quasi Maximum Likelihood firm fixed effects estimator is used. All specifications include the following additional variables, which are described in more detail in the data appendix: Sector Return$_{j,(t-2,t-4)}$, the interaction of this variable with Aggregate Uncertainty$_{j,t-2}$. Fixed capital and liquidity (working capital) are from Moody's. Robust standard errors clustered by firm are reported in parentheses: “a” is for significance at the 1 percent level “b” for the 5 percent level and “c” for the 10 percent level.
### Table 6A. Specific Sectors: Citation-Weighted Patents, 1930-32

<table>
<thead>
<tr>
<th></th>
<th>High Uncertainty</th>
<th>Low Uncertainty</th>
<th>Consumer Durables</th>
<th>Non. Cons. Durables</th>
<th>Intermediate Inputs</th>
<th>Final Goods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector Return&lt;sub&gt;j,t-1&lt;/sub&gt;</td>
<td>-8.388</td>
<td>-6.022</td>
<td>3.463</td>
<td>4.802</td>
<td>4.549</td>
<td></td>
</tr>
<tr>
<td>Sector Uncertainty&lt;sub&gt;j,t-2&lt;/sub&gt;</td>
<td>0.213</td>
<td>0.246</td>
<td>0.210</td>
<td>0.198</td>
<td>-0.082</td>
<td>-0.203</td>
</tr>
<tr>
<td></td>
<td>[0.572]</td>
<td>[0.305]</td>
<td>[0.216]</td>
<td>[0.192]</td>
<td>[0.342]</td>
<td>[0.385]</td>
</tr>
<tr>
<td>Sec. Return&lt;sub&gt;j,t-1&lt;/sub&gt; x Sec. Uncertainty&lt;sub&gt;j,t-2&lt;/sub&gt;</td>
<td>4.171</td>
<td>2.453</td>
<td>4.089</td>
<td>-3.539</td>
<td>3.839</td>
<td>0.688</td>
</tr>
</tbody>
</table>

Firms: 153 236 147 242 88 155
Sectors: 884 1 2 56
Year Dummies: Yes Yes Yes Yes Yes Yes

### Table 6B. Specific Sectors: Citation-Weighted Patents, 1933-36

<table>
<thead>
<tr>
<th></th>
<th>High Uncertainty</th>
<th>Low Uncertainty</th>
<th>Consumer Durables</th>
<th>Non. Cons. Durables</th>
<th>Intermediate Inputs</th>
<th>Final Goods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector Return&lt;sub&gt;j,t-1&lt;/sub&gt;</td>
<td>-1.373</td>
<td>-1.584</td>
<td>-2.980</td>
<td>-0.651</td>
<td>-4.560</td>
<td>-1.998</td>
</tr>
<tr>
<td></td>
<td>[1.363]</td>
<td>[1.667]</td>
<td>[1.519]b</td>
<td>[0.849]</td>
<td>[2.672]c</td>
<td>[2.427]</td>
</tr>
<tr>
<td>Sector Uncertainty&lt;sub&gt;j,t-2&lt;/sub&gt;</td>
<td>-0.304</td>
<td>-0.459</td>
<td>-0.915</td>
<td>-0.138</td>
<td>-0.917</td>
<td>-0.336</td>
</tr>
<tr>
<td></td>
<td>[0.280]</td>
<td>[0.268]c</td>
<td>[0.275]a</td>
<td>[0.198]</td>
<td>[0.522]c</td>
<td>[0.401]</td>
</tr>
<tr>
<td>Sec. Return&lt;sub&gt;j,t-1&lt;/sub&gt; x Sec. Uncertainty&lt;sub&gt;j,t-2&lt;/sub&gt;</td>
<td>0.051</td>
<td>0.383</td>
<td>1.004</td>
<td>0.146</td>
<td>0.996</td>
<td>0.470</td>
</tr>
<tr>
<td></td>
<td>[0.328]</td>
<td>[0.605]</td>
<td>[0.377]a</td>
<td>[0.187]</td>
<td>[0.628]</td>
<td>[0.842]</td>
</tr>
</tbody>
</table>

Firms: 180 265 144 301 105 160
Sectors: 884 1 2 56
Year Dummies: Yes Yes Yes Yes Yes Yes

Notes: The dependent variable is an annual count of citation-weighted patents for firm i in sector j at time t. A Poisson Quasi Maximum Likelihood firm fixed effects estimator is used. All specifications include the following additional variables, which are described in more detail in the data appendix: Sector Return<sub>j(t-2),t-4</sub>, and the interaction of this variable with Aggregate Uncertainty<sub>t-2</sub>. Sector definitions are listed in the data appendix. Robust standard errors clustered by firm are reported in parentheses: “a” is for significance at the 1 percent level “b” for the 5 percent level and “c” for the 10 percent level.
Figure 1. The Cyclical Pattern of Patenting Activity, 1921-38

Notes: This figure plots the annual log difference of patents for all firms that patented in our dataset and for a balanced panel of 142 firms we observe patenting in every year. Real GDP is compiled using the series of Johnston and Williamson (2008). Gray shaded bars are NBER recession dates.

Figure 2. Patenting in Chemicals and Electrical Equipment Sectors, 1929-38

Notes: This figure plots the annual log difference of patents for firms in chemicals and electrical equipment sectors. Gray shaded bars are NBER recession dates.
Figure 3A and 3B. Standard Deviations of Aggregate and Sector-Level Returns

Notes: Aggregate series is the standard deviation of the mean daily return for equal-weighted (A) and value-weighted (B) market returns and the sector-level series is the standard deviation of mean returns for equal-weighted and value-weighted portfolios of firms in two-digit SIC sectors described in the Data Appendix.

Figure 4. The Geographic Location of R&D Labs, 1921-1938

Notes: Locations are addresses of the labs given in the NRC surveys. Observations are for labs that we were able to geocode. 1921 (568 labs), 1927 (1,158 labs), 1931 (1,886 labs), 1933 (1,888 labs), 1938 (2,217 labs).
Figure 5. Patenting Rates Across Sectors

Notes: Shares refer to the fraction of R&D labs that patent in each sector. Firms assigned to sectors based on a description of their R&D activities in the NRC surveys. The size of the circle is proportional to the number of firms in each sector.

Figure 6. Share of Patent Applications Cited, 1920-1939

Notes: Shares are for the population of successful patent applications in the European Patent Office’s PATSTAT database each year that are cited at least once in patents granted between February 1947 and September 2008.
Figure 7. Representation of the Updating Component by Uncertainty Percentile, 1930-1932

Notes: This figure show the effect of the updating component on citation-weighted patents at uncertainty percentiles evaluated at the mean sector return for the sub-period 1930-1932. It is calculated using the updating effect from columns 8 and 11 of Table 3.

Figure 8 Representation of the Updating Component by Uncertainty Percentile for Specific Sectors

Notes: This figure show the effect of the updating component from Table 6A and on citation-weighted patents for consumer durables and intermediate good sectors at each sectors’ uncertainty percentiles and mean sector returns for the sub-period 1930-1932.