AN EMPIRICAL EXAMINATION OF THE PROCYCLICALITY OF R&D INVESTMENT AND INNOVATION

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Abstract—The Schumpeterian opportunity cost hypothesis predicts that firms concentrate innovative activities in recessions. However, empirical evidence suggests that innovative activities are procyclical. Theory proposes that firms shift R&D investments and innovation from recessions to booms to maximize returns by capturing high-demand periods before imitators compete away rents. This paper provides the first empirical test of these predictions. Results indicate that R&D spending is more procyclical in industries with faster obsolescence, where matching invention to demand is more valuable, and innovation is more procyclical in industries with weaker IP protection, where imitation poses a greater threat.

I. Introduction

SCHUMPETER (1939) predicted that firms will concentrate investments in innovation in recessionary periods because activities to enhance productivity will carry lower opportunity costs when firm outputs are less in demand. This view has been generalized to predict that firms will shift resources toward productivity-enhancing activities, such as training and reorganization, and away from production activities in recessionary times, when the opportunity cost of doing so is lower (Hall, 1991; Saint-Paul, 1993; Aghion & Saint-Paul, 1998a, 1998b). Existing empirical evidence, however, documents a pattern of R&D investment and innovation that is decidedly procyclical (Barlevy, 2007; Comin & Gertler, 2006; Fatas, 2000; Geroski & Walters, 1995; Griliches, 1990). This pattern has been attributed to the financial constraints firms face during recessions (Aghion et al., 2010). Indeed, empirical evidence shows that firms' procyclical pattern of R&D investment is in part a reaction to the credit constraints present in recessionary periods (Aghion et al., 2012; Ouyang, 2010). In this paper, we build and test an alternative but complementary prediction: that R&D investment is procyclical because firms strategically time their innovations to coincide with economic booms, when higher demand makes it possible to capture more rents than during periods of lower demand.

We use prior theoretical arguments that attributed the procyclical pattern of innovation to firms purposefully delaying R&D investment (Barlevy, 2007) and innovation implementation (François & Lloyd-Ellis, 2003) until periods of high customer demand. While these models make different key assumptions, as described in section II, the common element driving their explanations of when firms invest and innovate is the anticipation that disclosing an innovation facilitates imitative rivalry. Imitation will reduce the rents the original innovator can capture. Anticipating this imitation, an innovating firm will maximize profits by timing the introduction of its innovation to match periods of higher demand. We empirically test this prediction by examining whether firms' R&D investments and innovation outcomes are more strongly procyclical in industries with weaker intellectual property protection, where imitation poses a greater threat to the appropriation of rents from innovation.

We also build on this theory to make predictions about how the procyclicality of R&D investments and innovation outcomes depends on the rate of product obsolescence in an industry. Just as imitation erodes expected profits from innovation, the value of an innovation decreases more quickly in industries where the rate of obsolescence is faster. However, the effect of obsolescence is different from the effect of imitation: imitation depends on an innovation being introduced to competitors, but obsolescence progresses even when innovations are withheld. When obsolescence progresses more rapidly, firms' incentives change. They now have more incentive to match R&D investment to high-demand periods and less incentive to withhold new innovations until the next period of high demand.

Our investigation makes three contributions to this literature. First, we empirically test whether the procyclical pattern of firm investments in R&D and patented innovations are moderated by the likelihood of imitation, as theory would predict. Second, we diverge from the unrealistic assumption that commercialization occurs contemporaneously with R&D investments and examine the patterns of R&D investment and innovation patenting separately. Third, we extend this body of theory to make and test predictions about how the rate of product obsolescence affects the procyclicality of R&D investment and innovation.

Based on a panel data set of 7,754 public firms (and 4,157 firms for the innovation analysis) from 1975 to 2002, we find confirmatory evidence that R&D investments and patented innovations are strongly procyclical. We use the Carnegie Mellon survey data (Cohen, Nelson, & Walsh, 2000) to create measures of the strength of intellectual property rights that protect inventors from imitation and the rate at which an industry's innovations are rendered obsolete by rival innovations. We find that R&D investments are more procyclical in industries with faster obsolescence and that innovations are more procyclical in industries with weaker patent protections, even after controlling for the extent of financial constraint in the industry. Overall, our analysis suggests that the timing of R&D investment is separate from decisions on innovation are separate decisions, and that firms adjust innovation, rather than R&D investment, in response to the threat of imitation.

This observation carries interesting implications for policy as well. Barlevy (2007) concluded from his theoretical model that shifting R&D investment from periods of low

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demand to periods of high demand would increase the social welfare cost of economic downturns, thereby justifying policy initiatives to improve social welfare by encouraging countercyclical R&D investment. Our empirical results suggest these interventions may be the most necessary in industries where the rate of obsolescence is fastest, because firms in these industries have greater incentive to delay R&D spending. Our results also suggest that firms are less likely to shift innovation to periods of high demand when patent protection is stronger. To the extent that new introductions drive increases in consumption, increasing the strength of intellectual property protection may help promote faster recovery during downturns.

The remainder of the paper is organized as follows. Section II describes existing theories that attribute procyclical R&D investment to a demand-matching strategy and presents four hypotheses. Sections III and IV describe our empirical model and our data set. Section V shares and discusses our empirical results. Limitations are discussed in Section VI. Section VII concludes with a summary of the main findings and with suggestions for future research.

II. Theory and Hypotheses

The demand-matching theoretical explanation for the procyclicality of R&D investment and innovation is founded on the desire of profit-maximizing innovators to time their innovative activities to periods of high demand: they heavily discount future returns to innovations, so they want to appropriate returns in periods when the potential for returns is greatest (Barlevy, 2007; François & Lloyd-Ellis, 2003; Shleifer, 1986). As a result, R&D spending and innovation outcomes are shifted from periods of low demand to periods of high demand, a result that runs contrary to the socially optimal pattern of countercyclical investment in periods of low opportunity cost.

The process of generating new product introductions involves many potentially separate activities.[1] Firms engage in research to identify problems to solve and search for solutions. When successful, this generates an invention. Further development, testing, refinement, design, manufacturing, and marketing take place before the invention is transformed into a commercialized innovation. At some point between an innovation's invention and its commercialization, firms often apply for a patent, which requires that the invention be developed enough to claim usefulness (as well as novelty and nonobviousness) and constitute the reduction to practice. Although investing in R&D and choosing to develop inventions into commercialized innovation are separate strategic decisions, the aggregate empirical evidence used to examine the procyclicality of innovation has so far failed to consider them separately. We draw on the existing theoretical literature to make testable predictions about both investments in R&D and the generation of patented innovations.

We test the demand-matching prediction by first using existing theory to predict industry characteristics that should be associated with a larger incentive for firms to match innovative activity to periods of high demand and then testing whether patterns in the data are consistent with those predictions. Our efforts are complicated by the fact that the theoretical models of demand matching have made different assumptions about the separability of R&D investments and the commercialization of resulting inventions. Barlevy (2007) assumes that R&D and innovation are contemporaneous because firms are "impatient" and introduce new inventions immediately. François and Lloyd-Ellis (2003) and Shleifer (1986) assume that decisions on the timing of R&D and innovation are separate ones, so that firms can invest in R&D to generate inventions and then strategically delay that invention's commercial introduction. The different assumptions result in different predictions about the timing of R&D investments during the business cycle; the predictions with respect to the timing of innovation are consistent, and so we begin with those.

Consider first the theoretical model proposed by Barlevy (2007), who assumes that firms commercialize innovations immediately upon discovery, such that the timing of R&D investments completely determines the timing of innovation. Barlevy models a firm's choice of the level and timing of R&D investment (and hence innovation) based on expected returns from those innovations. Innovating firms anticipate both business cycle fluctuations and profit erosion by imitative rival firms, which develop new innovations based on the innovation of the focal firm.

Shleifer (1986) presents a theory similar to Barlevy's (2007) but focuses on the implementation or commercialization of new technologies rather than on R&D investment. In his model, inventions are exogenously generated and arrive at uniform intervals over time. Innovators time implementation of an innovation to maximize expected profits, which are limited by the entry of imitative rivals who compete away the monopoly profits from the innovation. François and Lloyd-Ellis (2003) examine both investments in R&D and the introduction of resulting innovations. In their model, the creation of inventions (the R&D process) is endogenous, and inventions can be stored by keeping them secret, introducing the possibility of strategically delaying implementation. Once an innovation is introduced, knowledge about the innovation disseminates and leads to imitation or improvements that limit the period over which innovators capture monopoly profits. Innovators therefore

[1] We will refer to inputs to innovative activities as R&D and outputs of innovative activities as innovations. R&D is a process by which inventions are generated, and innovation is a process of introducing the inventions to the market, potentially including development, patenting, and commercialization. This is consistent with the three stages of a new technology entering the marketplace described by Schumpeter (1942): invention, innovation, and diffusion. We focus on the first two of these, and note that while Schumpeter held that innovation (i.e., commercialization of a new product or process) may occur without a firm inventing a new product or process, our paper will focus on innovation based on the firms' own inventions.

time the implementation of innovations to periods of high demand.

In all of these theoretical models, an innovation introduced into the market by a focal firm facilitates imitation by competitors because innovations are assumed to become public knowledge as soon as they are discovered and introduced. Rival imitators use the focal firm's innovation to develop the next generation of the innovation. The competing innovation by a rival then competes with or replaces the focal firm's innovation, thereby reducing or eliminating rents for the focal firm. Because innovators with the most advanced technology earn greater profits, the timing of a focal firm's innovation has direct consequences for the timing of rent-decreasing competition from its rivals. An innovating firm that anticipates an imitation will expect a limited period during which it can enjoy monopoly rents. Thus, our primary prediction is that firms will shift innovation toward periods of higher demand in order to maximize the returns from innovation captured before imitators compete away monopoly rents.

A key driver of the incentive to match innovation to high-demand periods in these models is the anticipated erosion of monopoly profits by imitators. All else equal, firms anticipating faster imitation from rivals will have stronger incentives to match an innovation to periods of high demand, relative to firms anticipating slower imitation from rivals. Faster imitation shortens the period over which a firm expects to capture rents from innovation and increases the incentive to match that short period to a time of higher demand. When imitation is expected to be slow, a firm innovating in a downturn will expect to capture rents from an innovation through the subsequent boom period. Given that there is some nonzero discount rate applied to future profits, a firm facing slow imitation will have little incentive to delay innovation to wait for higher-demand periods.

We do not have data on product introductions, which would most closely match the idea of implementing an innovation, but we do have systematic and comprehensive data on the timing of firms' patent applications. While R&D investments determine the generation of inventions, the decision to patent the invention is potentially a separate strategic decision for the firm. Applying for a patent requires development to reduce the invention to practice and indicates a movement toward commercialization of the invention. Because the U.S. patent system has been historically (until 2011) based on a first-to-invent criterion for inventorship and because patent protection is for a fixed period of time that begins with the patent application, firms had an incentive to delay patenting until closer to commercialization. Patented inventions therefore represent further development and commercialization of an invention, bringing an invention closer to implementation. The event of patenting an invention also corresponds well with the theoretical importance of disclosing an invention. In the theories described above, implementation fosters imitative rivalry because it makes knowledge of the invention public and accessible to rival firms. In reality, an invention is disclosed when it is patented, so the decision to patent an invention involves the decision to provide information to rivals.

Based on these theories, which universally posit that firms match innovative activity to periods of high demand in order to forestall imitation and capture greater profits, we expect that the procyclical pattern of innovation is more pronounced when the intellectual property protection for patented inventions is weaker, making imitation more of a threat. In theory, patent protection guarantees a temporary monopoly position for innovators to appropriate returns to their innovations, protecting innovators from the effects of imitation. However, Cohen et al. (2000) find that the effectiveness of patents in appropriating the rents from innovation varies tremendously across industries. We explore whether the reduction (increase) in innovation in periods of downturns (upswings) is greater for firms in industries with weaker intellectual property (IP) protection—where the imitation of new innovations would be faster and therefore more damaging to the profitability of the focal innovation—than for firms in industries with stronger IP protection.

Hypothesis 1: The production of patented inventions will be more sensitive to changes in demand for firms in industries with weaker patent protection, relative to firms in other industries, all else equal.

A. *Timing of R&D Investments*

Whereas the models predict a common pattern of procyclical innovation, their differing assumptions result in varied predictions for the pattern of R&D investment. As noted above, Barlevy assumes that R&D and innovation are contemporaneous, so the incentive for firms to match innovations with periods of high demand results in procyclical R&D investments. Shleifer (1986) and François and Lloyd-Ellis (2003) allow for a delay between R&D investment and the firms' strategically selected introduction of an innovation. If an innovating firm can keep an invention secret until it is introduced, and thereby delay its imitation by competing firms, there is no incentive to shift R&D expenditures to periods of high demand. We therefore examine whether the procyclical pattern of R&D investments is more pronounced when the intellectual property protection for patented inventions is weaker, making imitation more of a threat. If based on Barlevy's maintained assumption, the prediction is as follows:

Hypothesis 2: R&D investment will be more sensitive to changes in demand for firms in industries with weaker patent protection, relative to firms in other industries, all else equal.

Note that the alternative hypothesis, that R&D procyclicality does not depend on the strength of patent protection, will hold under the alternative assumption that R&D and innovation are separate in terms of timing. In fact, by allowing investment in R&D to be decoupled from the implementation of innovations, François and Lloyd-Ellis (2003) predict that firms will engage in more R&D during recessions, making R&D investments countercyclical, and will delay implementing the resulting innovations until boom periods, making innovation procyclical.[2]

B. *Obsolescence*

While Barlevy (2007) credits imitation by rivals with eroding an innovator's monopoly profits, the critical aspect of the theoretical model is that profits from an innovation are expected to decrease in years subsequent to its introduction. This general idea can be extended to consider the effect of product obsolescence on the timing of R&D and innovation. While both imitation and obsolescence reduce the profitability of a given innovation over time, obsolescence differs from imitation because imitation is facilitated by the focal innovation's introduction. Imitation is therefore responsive to the innovation timing decisions of the focal innovator. Obsolescence is driven by collective knowledge accumulation and technological development, and it progresses whether or not any particular innovator introduces his or her innovations. Faster obsolescence makes a focal innovation less profitable in the future than it is on the day it is invented, regardless of when the innovator chooses to introduce it.

Obsolescence therefore creates different incentives for the timing of R&D investment and innovation. The effect of obsolescence is to decrease the incentive to delay the introduction of an innovation (once invented) to wait for periods of higher demand. It therefore affects only the timing of innovation if the timing decisions with respect to R&D investment and innovation implementation are separate. This gives the firm additional incentive to match R&D investments to periods of high demand in order to generate the inventions when they can be introduced quickly and decreases its incentive to delay introducing an innovation (once discovered), to avoid eroding its value.

We therefore predict that in industries with higher rates of obsolescence, firms will be less likely to delay the introduction of innovations to high demand periods. When obsolescence is slower, firms may elect to delay the introduction of inventions:

Hypothesis 3: The production of patented inventions will be less sensitive to changes in demand for firms in industries with faster obsolescence of products, relative to firms in other industries, all else equal.

We also expect that in industries with higher rates of obsolescence, firms will be more likely to shift R&D investments to periods of high demand:

Hypothesis 4: R&D investment will be more sensitive to changes in demand for firms in industries with faster obsolescence of products, relative to firms in other industries, all else equal.

However, we note that to the extent that firms shift R&D investments to periods of high demand when there is a faster rate of obsolescence, as predicted above, innovation patterns will be explained by the timing of R&D investment. In other words, rapid obsolescence would provide no additional incentive to shift the introduction of innovation beyond the incentive to shift the timing of R&D investments. At the same time, when obsolescence is slow, firms may elect to invest in R&D in lower demand periods (consistent with hypothesis 4) and select the timing of innovation introduction to maximize rents.

III. Empirical Methodology

We estimated two equations to determine the effect of changes in industry demand on innovative activities. First, we modeled firm-level patent output to estimate the effect of changes in industry output on the number of inventions that firms patent. Second, we modeled the annual firm-level expenditure on R&D to estimate the impact of changes in industry output on investments in R&D.

A. *Patent Output*

We adapted the empirical model of the patent production function (Hall, Griliches, & Hausman, 1986; Pakes & Griliches, 1980) to include a measure of annual industry output to test our predictions. Given the count nature of the dependent variable, we relied on the Poisson quasi-maximum likelihood estimator (Wooldridge, 1999) to estimate the following equation:

$$E[P_{kt}|X_{it}, Z_{kt-1}] = \exp[\beta_1 RD_{kt-1} + \beta_2 X_{it} + \beta_3 M_{kt-1} + \tau_t + \mu_k],$$

where P_{kt} is the number of patents that firm k in industry i applied for in year t, X_{it} is a natural log of output in industry i, Z_{kt-1} is a vector including the natural log of R&D spend-

[2] In a later paper, François and Lloyd-Ellis (2009) feature implementation delays but determine that R&D investment is procyclical. They separate the innovative activity into three distinct stages: research activity (R&D), matching research output (ideas) to potential applications, and implementing ideas in the marketplace. The strategic decisions of firms with respect to innovations as output of the R&D process are determined by the expected returns from innovations. The authors theorize that R&D investment is procyclical because the expected value of unmatched ideas is highest during booms, so that entrepreneurs are dissuaded from investing in R&D during recessions. The matching of ideas to applications is countercyclical, because forward-looking entrepreneurs who expect the end of a recession engage in active search efforts during recessions to match ideas to potential commercial applications. Then, having matched the ideas to commercial applications, the entrepreneurs delay implementation until booms, when they can maximize their returns to the commercialized innovations.

ing in the previous year by firm k, RD_{kt-1}, and M_{kt-1}, a set of one-period lagged firm-level controls. The μ_k and τ_k are the firm and year effects, respectively.

This model estimates the relationship between R&D investments in the prior period and a firm's output of patented inventions in the year, consistent with prior literature. The estimated coefficient on the industry output variable X_{it} tests whether there is a significant change in the number of patents generated in a period as industry output increases or decreases. A positive estimated coefficient on X_{it} would indicate that, controlling for any change in R&D spending, firms generate more patented invention when industry output increases.[3]

In order to test how industry conditions (the rate of obsolescence and the strength of patent protection) affect the relationship between industry output growth and the number of patents a firm generates, we interacted industry output with the measures of patent effectiveness and obsolescence to test our predictions.

$$E[P_{kt}|X_{it}, Z_{kt-1}] = \exp[\beta_1 RD_{kt-1} + \beta_2 X_{it} + \beta_3 M_{kt-1} + \beta_4 X_{it} \times Obs + \beta_5 X_{it} \times Pateff + \tau_t + \mu_k].$$

A negative estimated coefficient (β_4) on the interaction of the rate of obsolescence (*Obs*) and industry output would be consistent with the expectation that patents will be less procyclical when the rate of obsolescence is faster. A negative estimated coefficient (β_5) on the interaction of the effectiveness of patent protection (*PatEff*) and industry output would be consistent with the expectation that innovation will be more procyclical with weaker patent protection.

C. R&D Investment

To estimate the effect of changes in output on changes in R&D spending, we used a first-differenced model of R&D investment (Barlevy 2007):

$$\Delta RD_{kt} = \beta_0 + \beta_1 \Delta M_{kt} + \beta_2 \Delta M_{kt-1} + \beta_3 \Delta X_{it} + \sum \tau_t + \omega_{kt},$$

where ΔRD_{kt} is a natural log of first-differenced investment in R&D by firm k in year t; ΔM_{kt} and ΔM_{kt-1} are vectors of contemporaneous and one-period-lagged, firm-level, first-differenced controls; ΔX_{it} is the change in industry output for year t and industry i; and τ_t are the year indicator variables. The model estimates the change in firms' R&D expenditures as a function of changes in firm-level characteristics, such as financial measures and physical capital, and common time effects. To the extent that output changes are correlated across industries, the aggregate business cycle effects will be captured by the year indicator variables. The estimated coefficient on industry output change variable ΔX_t captures the extent to which firms deviate from their average pattern of R&D growth in response to changes in industry demand conditions after accounting for other determinants of R&D. A positive, significant coefficient would provide support for the expectation of procyclical R&D spending: that firm R&D increases (decreases) in response to increasing (decreasing) industry output growth.[4]

As with the patent output model, we interacted the output growth variable with the industry-level indicators for obsolescence and patent protection. The modified model is as follows:

$$\Delta RD_{kt} = \beta_0 + \beta_1 \Delta M_{kt} + \beta_2 \Delta M_{kt-1} + \beta_3 \Delta X_{it} + \beta_4 \Delta X_{it} \times Obs + \beta_5 \Delta X_{it} \times PatEff + \sum \tau_t + \omega_{kt}.$$

A positive estimated coefficient (β_4) on the interaction of changes in output and the measure of rate of obsolescence (*Obs*) would suggest that change in R&D spending for a given change in output is larger for firms in industries with faster obsolescence than for firms in other industries, providing evidence of a more-pronounced demand-matching behavior in R&D investments among firms in industries with faster obsolescence. Likewise, a negative estimated coefficient (β_5) on the interaction of changes in output and the measure of patent effectiveness (*PatEff*) would suggest that change in R&D spending for a given change in output is smaller for firms in industries with stronger patent protection than for firms in other industries, providing evidence of more pronounced demand-matching behavior in R&D investments among firms in industries with weaker patent protection.

IV. Data and Variables

We combined data from four sources to create a novel data set. We obtained industry-level annual demand data from the NBER Manufacturing and Productivity database (Bartelsman & Gray, 1996).[5] We used results from the Car-

[3] Tests for serial correlation and heteroskedasticity on the model prior to mean-differencing confirmed the existence of both: a Wooldridge test for autocorrelation resulted in F (1, 4139) = 89.74, which corresponds to a p-value of 0.000. This rejects the null hypothesis of no first-order autocorrelation. A Breusch-Pagan test for heteroskedasticity produced a chi-square statistic equal to 247,052.66, with a p-value of 0.000, which strongly rejects the null hypothesis of constant variance. Therefore, we used firm fixed effects and provide robust standard errors, clustered by firm.

[4] We estimated the model using OLS on level variables (before first-differencing) and performed tests for autocorrelation and heteroskedasticity. Tests for serial correlation and heteroskedasticity indicated evidence for both. A Wooldridge test for autocorrelation resulted in F (1, 6823) = 1,858.92, which corresponds to a p-value of 0.000. This rejects the null hypothesis of no first-order autocorrelation. A Breusch-Pagan test for heteroskedasticity produced a chi-square statistic equal to 6,355.65, with a p-value of 0.000, therefore strongly rejecting the null hypothesis of constant variance. We used OLS regression with first-differenced variables and clustered standard errors to mitigate these issues. A Durbin-Watson test on the first-differenced model did not indicate any substantial remaining autocorrelation.

[5] Barlevy (2007) used the same data to measure annual industry output and noted the limitation that it includes only manufacturing industries. Because our measures based on survey data also cover only manufacturing industries, we do not supplement these output data with other data to capture nonmanufacturing industries.

TABLE 1.—VARIABLE DESCRIPTIONS AND SOURCES

Variables	Description	Level	Data Source
Endogenous Variables			
Delta_R&D	First difference of the natural log of R&D expenditures	Firm-year	Compustat
NumPats	Count of patented inventions	Firm-year	NBER Patent Data
Explanatory Variables			
Delta_Cash flow	First difference of the natural log of firm's cash flow, calculated by adding depreciation and amortization (DP) and income before extraordinary items (EB)	Firm-year	Compustat
Delta_Total Assets	First difference of the natural log of firm's total assets	Firm-year	Compustat
Delta_Total Liabilities	First difference of the natural log of firm's total liabilities	Firm-year	Compustat
Delta_LT Debt	First difference of the natural log of firm's long-term debt	Firm-year	Compustat
Delta_ST Debt	First difference of the natural log of firm's net property, plant, and equipment	Firm-year	Compustat
Delta_Capital Stock	First difference of the natural log of firm's short-term debt	Firm-year	Compustat
Delta_R&D_Lag	First difference of the natural log of R&D expenditures, lagged one period	Firm-year	Compustat
ln R&D (lag)	One-period lagged natural log of R&D expenditures	Firm-year	Compustat
ln Sales (lag)	One-period lagged natural log of revenues	Firm-year	Compustat
ln Emp (lag)	One-period lagged natural log of number of employees	Firm-year	Compustat
ln PPE (lag)	One-period lagged natural log of value of property, plant, and equipment	Firm-year	Compustat
Delta_Output	First difference of the natural log of industry real gross output	Industry-year	NBER Manufacturing and Productivity data
ln Output	Natural log of industry output	Industry-year	NBER Manufacturing and Productivity data
Obsolescence	Average survey response to rate of introduction of innovations	Industry	Carnegie Mellon survey
Patent effectiveness	Average survey response to degree of effectiveness of patent protection	Industry	Carnegie Mellon survey
External financing	Extent of industry reliance on external financing	Industry	Compustat

negie Mellon survey (CMS) of R&D managers (Cohen et al., 2000) to measure the proposed relevant industry-level characteristics: the rate of obsolescence, and the effectiveness of patent protection. The CMS survey sampled the population of all R&D labs located in the United States conducting R&D within manufacturing industries as part of manufacturing firms in 1994. The survey sampled 3,240 labs and received 1,478 responses, for an adjusted response rate of 54% (Cohen et al., 2000). The data were aggregated to the industry-level[6] and refer to the period 1991 to 1993, roughly the middle of the period used in our analysis. It is worth noting that the firms responding to the survey were public and private firms, categorized into industries according to the self-reported industry focus as the lab level, whereas the firms in our analysis are only public firms (for data availability reasons) and are considered at the firm (not lab) level.

To construct the sample of firms to estimate the patent model, we started with all firms listed in Compustat from 1975 to 2002. We matched the Compustat data with NBER Patent Data (Hall, Jaffe, & Trajtenberg, 2001) based on the unique company identifier available in Compustat (the dynamically assigned gvkey) to develop a data set containing all patented inventions (and accompanying patent characteristics) for each public, Compustat-covered company for which patents could be identified. After keeping observations for firms that had a nonmissing number of patents and dropping observations that had missing values for control variables, the data contained 64,236 firm-year observations. We dropped 266 observations with only one firm-year observation per firm, and we dropped 1,166 firms (8,980 observations) due to zero patents for all years in the sample. This provided a data set covering 747,034 patents by 4,274 firms in 117 different three-digit SIC code industries. Matching further with the CMS survey to obtain industry characteristics limited the useful data set, resulting in an unbalanced data set of 48,477 firm-year observations reflecting 711,570 patents by 4,029 firms in 101 different manufacturing industries in 1975–2002. Table 1 provides variable descriptions and data sources.

The data set for the R&D model was also developed using Compustat data for all firms listed in the 1975–2002 period. We matched these firms by industry (using three-digit SIC code) to the NBER Manufacturing and Productivity database to obtain the industry-level annual output data for the same period. After keeping observations for firms that had nonmissing values for R&D expenditures and the necessary control variables for a given firm-year, the resulting unbalanced sample consists of 75,093 observations and contains data for 8,165 firms in 118 different manufacturing industries (as identified by three-digit SIC codes). Matching the sample to the CMS survey limits the data set because some of the SIC codes are not represented in the survey

[6] The survey asked R&D lab managers questions about the principal industry for which the R&D lab was conducting research.

data. The result is a set of 71,264 observations representing 7,731 firms in 102 manufacturing industries.

A. Construction of Variables

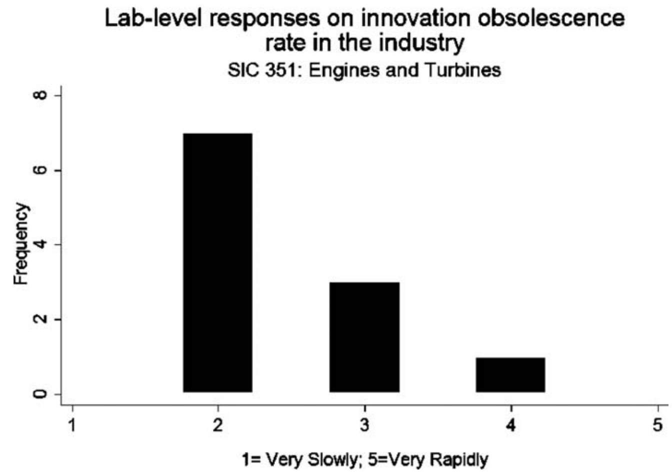
Patent counts. We used a count of patented inventions in each firm-year observation, NumPats, as the dependent variable in the innovation model. This is a standard measure of inventive outcome for the firm. We used the application date of the patent provided in the NBER database to assign a time to the invention.

R&D growth. Compustat provides annual data on firm-level R&D expenditures. We first-differenced the natural log of annual R&D expenditures for each firm to obtain annual R&D growth levels (Barlevy, 2007) that we used as our dependent variable in the R&D equation (Delta_R&D).

Industry output growth. We followed Barlevy (2007) in constructing an industry output growth measure. We obtained nominal gross output by summing annual value-added and materials costs for each of the three-digit SIC industries in the sample, as provided by the NBER Manufacturing and Productivity database (Bartelsman & Gray, 1996). We calculated the annual real gross output for each industry by dividing the nominal gross output by each industry's shipments deflator, also provided by the NBER Manufacturing and Productivity database. We used the first-difference of the natural log of real gross output in the R&D model as the industry demand growth variable (Delta_output). For the patent model, we used the natural log of the industry's real gross output as a measure of industry demand (ln Output).

Effectiveness of patent protection. The CMS survey asks the respondents the percentage of product and process innovations for which patenting was effective in protecting their firms' competitive advantage associated with those innovations. Responses fall into five mutually exclusive categories—$<$ 10%, 10–40%, 41–60%, 61–90%, and $>$ 90%—for product and process innovations separately. Following Arora and Ceccagnoli (2006), we constructed a patent effectiveness measure by computing a weighted average of the product and process scores, weighted by the percentage of R&D spent on product and process innovations. We averaged these scores at the industry level to construct the industry-level measure of patent effectiveness (Patent Effectiveness). Higher values of the measure indicate greater patent protection effectiveness in the industry, as perceived by the R&D managers based on their own experience with patenting, product introduction, and imitation by rivals. This industry-level measure from the same survey data has been used in other studies to investigate the relationship between the effectiveness of patent protection and licensing propensity, and to estimate returns to patent protections (Arora & Ceccagnoli, 2006; Arora, Ceccagnoli, & Cohen, 2008). To alleviate reporting bias concerns present with any self-reported measures, Arora et al. (2008) and Arora and Ceccagnoli (2006) use instrumental variables approach to further validate the measure. Additionally, Arora et al. (2008) provide an analysis of the correlation of the reported patent effectiveness with reported uses of patents and confirm that the reported patent effectiveness reflects the respondents' perceived net benefits of patenting, notably the prevention of copying.

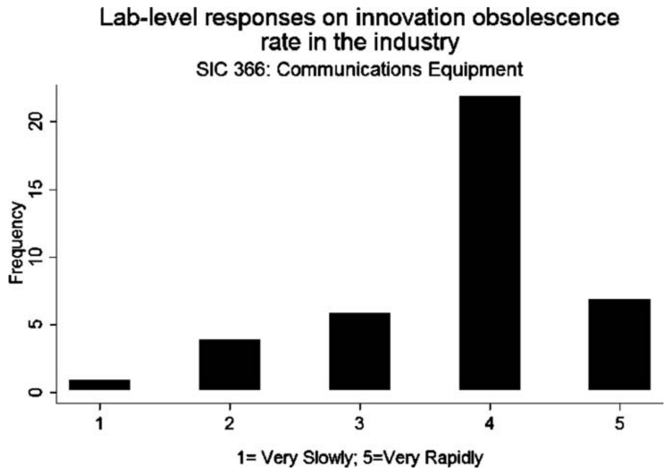
Figure 1.—Dispersion of Survey Responses for a Slow Obsolescence Industry



Rate of obsolescence. The CMS asks respondents to report the speed with which new product and process innovations are introduced in the focal industry. The lab-level survey responses indicate a categorical response for the speed of product (and process) innovations, ranging from Very Slowly to Very Rapidly, with Moderately in the middle. After coding each of the five responses numerically on a scale of 1 to 5 (with 1 being Very Slowly), we calculated a weighted average response for each lab with weights equal to the percentage of R&D spending reported for product and process innovation. Then we averaged these numerical scores at the industry level and constructed a measure of the average reported pace of obsolescence (Obs) in the industry.

Within an industry, lab-level responses to the survey questions obviously vary. Figure 1 provides a histogram of (weighted average) lab-level responses for an industry classified as having a relatively slow rate of obsolescence, SIC 351: Engines and Turbines. Figure 2 provides the histogram of responses for an industry classified as having a relatively fast rate of obsolescence, SIC 366: Communications Equipment. In both cases, there is some dispersion of responses, but the large majority of responses are consistent with the aggregate industry classification. These survey responses are consistent with industry analyst conclusions with regard to the rate of technological advance in these industries. An IBIS*World* industry report for the Engine and Turbine

FIGURE 2.—DISPERSION OF SURVEY RESPONSES FOR A FAST OBSOLESCENCE INDUSTRY



industry in the United States concludes that the industry is mature and characterized by established technology and processes (Hamilton, 2010). In contrast, the industry report on the Communication Equipment Manufacturing industry states that the industry is characterized by technological innovation and "rapid product introduction" (Waterman, 2012, p. 13).

Firm-level controls. In the R&D model, we controlled for firm's balance sheet items. Following Barlevy (2007), we included the following first-differenced natural logs of firm-level financial variables from Compustat: one-period-lagged and contemporaneous cash flow before R&D expenditures (Delta_Cash Flow),[7] contemporaneous and one-period-lagged measures of total assets (Delta_Total Assets), total liabilities (Delta_Total Liabilities), long-term and short-term debt (Delta_LT Debt and Delta_ST Debt), and capital stock (Delta_PPE).

In the patent model, we controlled for the firm's investment in R&D using the one-period-lagged natural log of R&D spending (ln R&D) (Blundell, Griffith, & Windmeijer, 2002; Hall et al., 1986); (Arora et al., 2008; Pakes & Griliches, 1980; Scherer, 1983). We controlled for the size of the company using the log of the total number of firm employees (ln EMP). We used the one-period-lagged natural log of firm plant, property, and equipment value to control for asset intensity (ln PPE), and we controlled for the impact of annual sales on patenting by including the one-period-lagged natural log of sales (ln SALES).

External financing. In both R&D and patent models, we controlled for industry dependence on external financing. Some industries rely on external financing more than their counterparts and are therefore more sensitive to fluctuations in the availability of external funds; this could directly affect firms' level of R&D spending and innovative output. Following Rajan and Zingales (1998), we constructed an industry-level measure of dependency on external financing by taking all Compustat firms in the years of our sample and calculating the total external funds needed to finance each firm's investments.[8] This sum, divided by the firm's total capital expenditures over the sample years, resulted in a ratio indicating a firm's level of dependence on external financing. Negative values indicate the availability of internal cash, and positive values indicate the need to finance investments externally. To obtain an industry-level measure of external financing dependence, we took the median value of the ratio for all firms in each three-digit SIC category (External Financing).

Time trends. We used year dummy variables to account for common time trends over the period 1975 to 2002, including broad technological changes (such as the growing importance of computing in R&D) and changes to patent policy that affected all firms. These indicators will also absorb any common changes in output across industries. If the business cycle of all industries is highly correlated, so that industry output grows and declines together across industries, these year indicators may leave little explanatory power for the industry-level output measure. We examine this empirically in our results.

B. *Descriptive Statistics*

Table 2 provides summary statistics for the key variables used in the analyses, and table 3 contains the correlations. The patent equation was estimated using a data set of 48,477 firm-year observations for 4,029 firms. The sample used for estimating the R&D equation contained 71,264 firm-year observations for 7,731 firms. All of the key variables show significant variation.

On average, firms in the sample applied for fourteen patents per year, but the median number of patents was one, indicating that many firms may not patent every year. Firm R&D spending fluctuations also varied. While on average firms change their R&D spending levels very little from year to year, many firms adjusted their annual R&D spending up and down by large amounts. The size of firms in the sample also varied significantly, with a median of 881 employees and observations containing up to 877,000 employees. The average rate of obsolescence in our sample is about 3, which corresponds to the rate of new product

[7] We constructed our variable for cash flow before R&D expenditures by adding the depreciation and amortization (DP) and income before extraordinary items (IB) reported in Compustat.

[8] Total external funds needed is equal to total capital expenditures minus net cash flow from operations, which is calculated by adding decreases in inventories, decreases in account receivables, and increases in account payables to cash flow from operations. Note that these items are available for cash flow statements with format codes 1, 2, or 3. For format code 7, we calculated the sum of income before extraordinary items, depreciation and amortization, deferred taxes, equity in net loss/earnings, sale of property, plant and equipment and investments/gain (loss), and funds from operations/other.

Table 2.—Descriptive Statistics

	N	N (firms)	Mean	Median	SD	Minimum	Maximum
A. Patenting Estimation							
Endogenous Variables							
NumPats	48,477	4,029	14.65	1	76.54	0	2,655
Explanatory Variables							
ln R&D (lag)	48,477	4,029	4.84	5.46	3.29	0	13.76
ln Sales (lag)	48,477	4,029	9.12	9.41	3.10	0	16.84
ln Emp (lag)	48,477	4,029	1.07	0.61	1.20	0	6.78
ln PPE (lag)	48,477	4,029	7.72	7.77	2.94	0	16.08
ln Output	48,477	4,029	8.99	8.81	1.09	5.79	12.37
Obsolescence	48,477	4,029	2.85	2.87	0.35	2	4
Patent effectiveness	48,477	4,029	0.46	0.45	0.15	0.05	0.82
External financing	48,477	4,029	0.55	−0.10	1.59	−2.93	4.76
Year						1975	2002
B. R&D Estimation							
Endogenous Variables							
Delta_R&D	71,264	7,731	0.11	0	1.09	−11.69	12.94
Explanatory Variables							
Delta_Cash flow	71,264	7,731	0.01	0.02	0.51	−8.53	8.30
Delta_Total assets	71,264	7,731	0.18	0.03	1.33	−14.64	14.57
Delta_Total liabilities	71,264	7,731	0.18	0.02	1.31	−13.93	14.29
Delta_LT debt	71,264	7,731	0.12	−0.01	1.74	−12.95	13.64
Delta_ST debt	71,264	7,731	0.09	0	1.62	−13.99	14.22
Delta_Capital stock	71,264	7,731	0.15	0.01	1.17	−13.97	14.00
Delta_R&D_lag	71,264	7,731	0.14	0	1.10	−11.69	12.94
Delta_Output	71,264	7,731	0.04	0.04	0.11	−0.53	1.12
Obsolescence	71,264	7,731	2.84	2.87	0.35	1.56	4
Patent effectiveness	71,264	7,731	0.44	0.44	0.15	0.05	0.82
External financing	71,264	7,731	0.33	−0.14	1.39	−2.93	4.76
Year						1975	2002

introductions to being rated as Moderately. Industries with the lowest rate of obsolescence were Asphalt Paving and Roofing Materials (SIC 295) with a score of 1.56, Pulp Mills (SIC 261) with 1.80, and Engines and Turbines (SIC 351) with 2.23. Industries in which respondents reported relatively fast rates of obsolescence included Computer and Office Equipment (SIC 357), with a score of 4; Communications Equipment (SIC 366), with 3.25; and Meat Products (SIC 201) with a score of 3.14. The patent effectiveness measure ranges from 5% to 82%, indicating a wide variation of patent protection strength across industries. Among the industries that obtained a higher patent effectiveness were Transportation Equipment (SIC 379) with 82%, and Pharmaceuticals (SIC 283) and Medical Devices (SIC 384), each with 69%. Industries that obtained the lowest patent effectiveness score of 5% were Cigarettes (SIC 211), Textiles (SIC 239), and Periodicals and Newspapers (SIC 271, 272).

V. Empirical Results

A. *Results for Innovation Model*

Table 4 reports the results from estimations of the patent models. The first column reports the results of estimating a model with control variables and the demand measure but not lagged R&D. The results confirm that innovation, as measured by patented inventions, was procyclical. It is possible that this pattern could be due entirely to a procyclical pattern of R&D investments and immediate patenting, as in Barlevy's model. The second column reports results controlling for one- and two-year lagged firm R&D investment. The estimated coefficient on (one-year) lagged R&D investments is positive and highly significant, indicating that R&D and patenting are highly correlated over time. However, the magnitude of the estimated coefficient on output was only slightly reduced by the addition of the R&D control, suggesting that the procyclicality of innovation is at least partly due to factors other than the underlying timing of R&D investments. In order to control for common effects of business cycles across industries, we included year dummies in the third model. This reduced the estimated coefficient on the output variable only slightly, consistent with the small impact of common time trends in the R&D equation discussed below.

The fourth column reports a model including the interaction of an industry's patent effectiveness measure with its industry output variable (Output × Patent Effectiveness). Hypothesis 1 predicted that firms in industries with stronger patent protection would not be as sensitive to threats of imitation and would therefore have a weaker incentive to match the timing of innovation to periods of high demand. Results show that the number of innovations generated by firms in industries where patents afford more effective protection against imitators fluctuated less with the business cycle, consistent with this prediction. When patent effectiveness was at its (in-sample) maximum, the number of patented innovations did not vary with changes in industry output.

TABLE 3.—CORRELATIONS (N = 48,477)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Delta_R&D	1																		
2	NumPats	−0.01	1																	
3	Delta_Cash Flow	**0.05**	0.00	1																
4	Delta_Total Assets	**0.52**	**−0.01**	**0.13**	1															
5	Delta_Total Liabilities	**0.52**	**−0.01**	**0.13**	**1.00**	1														
6	Delta_LT Debt	**0.50**	**−0.01**	**0.10**	**0.90**	**0.90**	1													
7	Delta_ST debt	**0.25**	0.00	**0.05**	**0.47**	**0.47**	**0.56**	1												
8	Delta_Capital Stock	**0.17**	0.00	**0.02**	**0.30**	**0.30**	**0.35**	**0.31**	1											
9	Delta_R&D_Lag	**0.50**	**−0.01**	**0.12**	**0.90**	**0.90**	**0.86**	**0.51**	**0.33**	1										
10	ln R&D (lag)	**−0.08**	0.00	−0.01	**0.02**	**0.02**	0.00	**−0.01**	0.00	**0.03**	1									
11	ln Sales (lag)	**−0.16**	**0.31**	0.00	**−0.13**	**−0.13**	**−0.12**	**−0.06**	**−0.04**	**−0.12**	**0.16**	1								
12	ln Emp (lag)	**−0.20**	**0.26**	0.00	**−0.31**	**−0.31**	**−0.29**	**−0.13**	**−0.08**	**−0.28**	**−0.02**	**0.41**	1							
13	ln PPE (lag)	**−0.07**	**0.39**	0.00	**−0.11**	**−0.11**	**−0.10**	**−0.04**	**−0.02**	**−0.11**	**−0.04**	**0.44**	**0.77**	1						
14	Delta_output	**−0.17**	**0.28**	0.00	**−0.28**	**−0.28**	**−0.26**	**−0.12**	**−0.07**	**−0.27**	**−0.02**	**0.44**	**0.92**	**0.82**	1					
15	ln Output	**0.03**	**0.15**	0.00	**0.03**	**0.03**	**0.02**	0.00	−0.01	**0.02**	**0.03**	**0.20**	**0.07**	**0.08**	**0.10**	1				
16	Obsolescence	**0.05**	**0.03**	0.01	**0.04**	**0.04**	**0.04**	0.01	0.00	**0.04**	**0.05**	**0.07**	**−0.17**	**−0.15**	**−0.20**	**0.23**	1			
17	Patent effectiveness	**0.03**	**−0.02**	**−0.01**	**0.02**	**0.02**	**0.02**	0.01	0.00	**0.02**	**0.03**	**0.12**	**−0.24**	**−0.17**	**−0.20**	**−0.05**	**0.02**	1		
18	External financing	**0.05**	−0.01	**−0.01**	**0.04**	**0.04**	**0.04**	**0.01**	0.01	**0.04**	**0.05**	**0.17**	**−0.32**	**−0.22**	**−0.24**	**0.18**	**0.29**	**0.63**	1	
19	Year	**0.04**	**0.05**	**−0.01**	**0.05**	**0.05**	**0.05**	0.01	0.00	**0.04**	**0.05**	**0.15**	**−0.10**	**−0.11**	**−0.07**	**0.41**	**0.12**	**0.13**	**0.22**	1

Values in bold denote at least 5% significance level.

TABLE 4.—CONDITIONAL FIXED-EFFECTS POISSON ESTIMATES OF PATENT COUNTS EQUATIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Output	0.281***	0.272***	0.239***	0.670***	1.007**	0.787*	0.841*	0.961**
	(0.048)	(0.048)	(0.058)	(0.155)	(0.353)	(0.348)	(0.355)	(0.320)
Output × Patent Effectiveness				−1.125**		−0.962*	−1.473*	−0.946
				(0.417)		(0.461)	(0.620)	(0.529)
Output × Obsolescence					−0.231*	−0.054	−0.021	−0.106
					(0.110)	(0.127)	(0.129)	(0.114)
Output × External Financing							0.095	0.080
							(0.062)	(0.060)
ln R&D (lag)		0.035*	0.032*	0.032*	0.029*	0.031*	0.029*	0.032*
		(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
ln R&D (lag2)		0.019	0.020	0.022	0.022	0.022	0.021	0.020
		(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ln Sales (lag)	0.222**	0.206**	0.176*	0.195**	0.189**	0.195**	0.185*	0.213**
	(0.077)	(0.076)	(0.075)	(0.073)	(0.073)	(0.073)	(0.072)	(0.075)
ln Emp (lag)	0.128	0.116	0.159	0.192*	0.187*	0.194*	0.199*	0.146*
	(0.073)	(0.073)	(0.082)	(0.083)	(0.082)	(0.083)	(0.082)	(0.070)
ln PPE (lag)	0.170**	0.143*	0.128	0.088	0.087	0.084	0.083	0.107
	(0.065)	(0.065)	(0.073)	(0.071)	(0.070)	(0.069)	(0.068)	(0.062)
Year fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	No
N (observations)	48,477	48,477	48,477	48,477	48,477	48,477	48,477	48,477
N (firms)	4,029	4,029	4,029	4,029	4,029	4,029	4,029	4,029

Models 3 to 7 include year dummies, and all models include firm fixed effects. Robust standard errors, clustered by firm are in parentheses; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

TABLE 5.—OLS ESTIMATES OF GROWTH IN R&D EXPENDITURES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Delta_Output	0.211***	0.280***	0.202	−0.752**	−0.657*	−0.581	−0.625
	(0.032)	(0.035)	(0.121)	(0.267)	(0.299)	(0.351)	(0.358)
Output × Patent Effectiveness			0.222		−0.109	−0.245	−0.290
			(0.303)		(0.315)	(0.324)	(0.315)
Patent Effectiveness			0.175***		0.186***	0.107***	0.106***
			(0.025)		(0.025)	(0.031)	(0.032)
Output × Obsolescence				0.325***	0.309***	0.295**	0.297**
				(0.087)	(0.088)	(0.103)	(0.105)
Obsolescence				0.049***	0.051***	0.037**	0.040**
				(0.012)	(0.013)	(0.014)	(0.014)
Output × External Financing						0.060	0.085
						(0.066)	(0.066)
External Financing						0.013**	0.013**
						(0.004)	(0.004)
Delta_Cash Flow	−0.030*	−0.027	−0.027	−0.026	−0.025	−0.024	−0.026
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Delta_Cash Flow_Lag	−0.008	−0.009	−0.008	−0.008	−0.007	−0.006	−0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Delta_Total Assets	0.245***	0.244***	0.244***	0.244***	0.243***	0.243***	0.243***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Delta_Total Assets_Lag	0.085***	0.084***	0.083***	0.083***	0.082***	0.081***	0.081***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Delta_Total Liabilities	0.073***	0.073***	0.073***	0.074***	0.074***	0.074***	0.073***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Delta_Total Liabilities_Lag	−0.074***	−0.074***	−0.073***	−0.074***	−0.073***	−0.073***	−0.073***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Delta_LT Debt	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Delta_LT Debt_Lag	−0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Delta_ST Debt	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Delta_ST Debt_Lag	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Delta_Capital Stock	0.110***	0.109***	0.109***	0.109***	0.109***	0.109***	0.110***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Delta_Capital Stock_Lag	0.004	0.005	0.005	0.005	0.006	0.006	0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Constant	0.021***	0.021	−0.053**	−0.111**	−0.196***	−0.121*	−0.142**
	(0.003)	(0.018)	(0.020)	(0.039)	(0.044)	(0.050)	(0.049)
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes	No
N (observations)	71,264	71,264	71,264	71,264	71,264	71,264	71,264
R^2	0.22	0.22	0.22	0.22	0.23	0.23	0.22

The dependent variable is contemporaneous first-difference of natural log of R&D expenditures. The model uses first-differenced financial variables. Robust standard errors, clustered by firm, are in parentheses; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Results reported in column 5 test hypothesis 3, which predicted that firms in industries with faster obsolescence rates would match innovations to periods of high demand less than firms in other industries. The coefficient on the interaction (Output × Obsolescence) is negative and significant, suggesting smaller fluctuations in patented innovations with changes in industry output for firms in industries with faster obsolescence rates than for firms in other industries. However, the coefficient is not significant in the full model, reported in column 6. This is consistent with firms potentially concentrating R&D in periods of higher demand but not delaying innovation, when obsolescence is faster.

In column 7, adding a control for external financing dependency interacted with demand changes (Output × External financing) strengthened the key result: patenting was less sensitive to changes in demand in industries with stronger patent protection. The final column presents the results without the year fixed effects, which reduces the magnitude and significance level of the primary result. Although still negative, the coefficient on the interaction is significant at only the 7% level. This is not surprising, as the variation identifying the estimation is across industries, and the year indicators capture common variation across time that without these indicators swamps some of the cross-industry variation.

B. *Results for R&D Model*

Table 5 presents the results of estimating the R&D model. The first column reports a specification that included the control variables and the measure of output growth but excluded year indicators. These results confirm the procyclicality of R&D investment: the coefficient on the output variable is positive and significant at the 0.1% level. The estimation reported in the second column replicated this model, but also included year indicator variables, controlling for common trends that affect firms in all industries. The estimated procyclicality of R&D was not diminished by this set of controls, and the fact that the R^2 is unchanged by inclusion suggests that the common year trends do not have significant explanatory power across industries. Note that several of the control variables are significant, despite the fact that there is a high degree of correlation among these.[9]

The third column reports the results testing hypothesis 2, which predicted that R&D investments would be more sensitive to changes in demand in industries with weaker intellectual property protection. While there is some evidence that the average annual growth in R&D spending is larger for firms in industries with stronger patent protection, the estimated coefficient on the interaction of changes in demand with the indicator for industries with strong patent effectiveness (Output $\times$ Patent Effectiveness) is positive but not statistically significantly different from 0. This prediction is therefore not supported. However, recall from the discussion that if one assumes that R&D investments and innovation can be decoupled from each other, so that a firm is able to make separate timing decisions for each activity, the timing of R&D would not be expected to be sensitive to the threat of imitation.

The fourth column reports the results testing hypothesis 4, which predicted that R&D investments would be more sensitive to changes in demand in industries with faster obsolescence rates. This prediction is supported: the interaction of changes in demand with the indicator for industries with faster obsolescence (Output $\times$ Obsolescence) is positive and significant, indicating that R&D investments were more strongly procyclical in these industries.

The fifth column reports results for the full model, including both sets of interactions. The results are not altered substantially. The sixth column adds to the full model an industry-level control for reliance on external financing interacted with changes in demand (Output $\times$ External financing) in order to account for industries that might be financially constrained to a greater extent during recessionary periods. The main results hold. The final column replicates this model without the year fixed effects in order to examine whether the patterns change; they do not.

Recall that Barlevy's (2007) model that predicted procyclical investments in R&D was based on the anticipated imitation of an innovation subsequent to its introduction, and that this imitation could be delayed by delaying R&D and innovation (which were assumed to be simultaneous). Our results suggest that when firms anticipate that their innovations' profitability will be eroded by faster obsolescence, those firms are more likely to match their R&D investments to periods of higher demand. The lack of a significant moderating effect of patent effectiveness on the procyclicality of R&D investment is notable. If firms are able to separate the timing of R&D investments from the timing of product introductions, as in Shleifer (1986) and François and Lloyd-Ellis (2003), the timing of R&D would not be affected by the threat of imitation, because imitation (unlike obsolescence) can be delayed by delaying product introduction.

Together the results for R&D investments and innovation indicate that firms that strategically delay innovation when the threat of imitation is greater due to weaker IP protection,[10] and they shift the timing of R&D investments to meet higher demand in order to avoid inventions becoming obsolete before capturing rents. This analysis provides evidence that firms' decisions about the timing of R&D and innovation are discrete, with the potential for both optimizing the timing of R&D activities and strategically delaying innovations to maximize profits.

VI. Robustness to Alternate Measure of Obsolescence

Our survey-based measure of the rate of obsolescence in the industry is new to the literature. Although it is consistent with analyst reports, as noted above, its novelty dictates further validity testing. Existing studies provide an alternate measure of the "technology cycle time" in an industry. Narin (1994) defines the technology cycle time as the median age of the patents cited in other patents (the length of time between the cited patent and the focal citing patent).[11] As an example, he states that electronics, which is a "relatively fast moving area," has a much shorter cycle time than slower-moving areas such as mechanical areas. In slower technology-cycle-time industries, patented inventions are cited more slowly by new patented inventions and citation persists over a longer period because that initial technology is not yet obsolete, and therefore is still relevant as prior art. In contrast, in very fast technology-cycle-time industries, patented inventions become obsolete more quickly, and citations to the patented inventions are concentrated in the couple of years immediately following the invention.

We used the technology cycle time in an industry as an alternate measure of the pace of technological progress to validate our survey measure of obsolescence. In order to avoid endogeneity concerns, we used European (EPO) granted patents to calculate the technology cycle time for each industry. We downloaded data (from Thomson Innovation) on all granted European patents in international patent classes (IPCs) that are related to the SICs in the survey data.

[9] The equal and opposite coefficients on liabilities and lagged liabilities are not a result of colinearity in these variables. The coefficients are very similar if the model is estimated excluding one or the other measure.

[10] In unreported results, we experimented with regressing patents on R&D spending lagged by up to five years, and these lagged investments interacted with the measure of patent effectiveness, using a sample of positive output growth firm-years. We found that longer lags of R&D are more predictive of current patents in industries with weaker IP protection, consistent with the idea that firms will have more incentive to delay innovation implementation (evidenced by longer lags between R&D and innovation) when imitation threat is greater.

[11] Similarly, Trajtenberg et al. (1997) describe the average backward citation lag of a patent as a measure of the remoteness in time of the patent, where a longer lag corresponds to drawing from older sources.

For each patent, we collected data on all cited patents and calculated the backward citation lag as the time between cited and citing patent. We calculated the average backward citation lag for patents in each international patent class (IPC), and mapped the IPCs to the SICs in our sample using the concordance developed by Silverman.[12] This process provides the technology cycle time (the average backward citation lag) for 102 of the 105 SICs in our sample.

The range of the average backward citation lag was three to six years. To make interpretation easier, we inverted this measure[13] so that large values corresponded to shorter backward citation lags, consistent with a higher value from the survey responses, indicating faster introduction of innovation. The correlation between the (inverted) technology cycle time and the continuous measure for obsolescence from the survey is 0.44 and is significant at better than the 1% level. The substantial correlation between these two measures provides some confidence that the survey measure is in fact reflecting the rate of technological change in an industry.

To test the robustness of our results to this alternate measure, we replaced our survey measure of obsolescence with the technology cycle time in our estimations. The results with this alternate are completely consistent with the results using the survey measure described above, with the estimated coefficients nearly identical in terms of magnitude and significance.

VII. Limitations

This paper provides compelling new evidence about the demand-side mechanism driving the procyclicality of R&D and innovation, but it is not without limitations. First and foremost, our measure of innovation is the number of patent applications a firm generated in each year. While applying for a patent is a good indicator that a firm intends to develop its invention into a commercializable innovation, it remains removed from the decision to introduce the innovation in the marketplace. It is possible that firms would not delay patenting an invention but would delay its introduction to match demand patterns. In that sense, the patterns we document here may significantly understate the degree to which firms delay innovation in response to fluctuations in demand. However, because the theoretical predictions about the impact of imitation on the timing of innovation are driven by an invention's disclosure to imitative rivals (hence facilitating its imitation) and because patenting requires disclosure, we believe using patent dates to measure innovation timing is justifiable.

The second limitation is that we treat the industry conditions we consider—the rate of obsolescence and the threat of imitation—as exogenous and constant over the sample period. In reality, industry conditions are the products of complex competitive dynamics among industry rivals and are driven in part by the anticipation of and response to any single firm's R&D and innovation strategies. The survey data we used to create measures of obsolescence and the threat of imitation are based on R&D managers' impressions of industry conditions and therefore include the expected competitive dynamics in the industry. Nevertheless, we used static measures recorded in the middle of the time period studied, which will fail to capture changes in these conditions over time. We explored this empirically by reestimating our models using only the observations in years close to the survey data (including six years before and six years after the survey) and found results to be nearly identical to those reported here.

VIII. Conclusion

This paper provides an empirical analysis of the theories describing the demand-driven explanations for the procyclicality of R&D spending and innovation. We drew on this theory to make testable predictions about when procyclical innovation patterns will rise or wane. We tested for these patterns in a firm-level data set comprising thousands of firms across 100 manufacturing industries. In order to evaluate the competing predictions derived from different theoretical assumptions, we examined the procyclical patterns in R&D spending and patented innovations separately.

Our results are consistent with the expected procyclical patterns of R&D spending and innovation. We show that R&D spending was more procyclical in industries that report faster rates of obsolescence, but not in industries that report weaker patent protection. Innovation, meanwhile, was more procyclical in industries that report weaker patent protection, but not in industries that report faster obsolescence. These results are broadly supportive of the theoretical literature that predicts innovating firms will shift the timing of innovation to match market demand. They also support the feasibility of decoupling the timing of R&D investments from the timing of innovation. In doing this, we discovered that innovation timing, and not the timing of R&D investment, is affected by the threat of imitation by rivals.

The timing of R&D investment is affected by the rate of obsolescence. When the rate of obsolescence is low, so that inventions do not lose too much value when their development and commercialization is delayed, firms are able to make R&D investments in recessionary periods but withhold commercialization until demand increases. However, when the rate of obsolescence is high, firms move R&D activities to periods of higher demand and introduce innovations more closely in time with the R&D investment. Hence, we see more procyclical R&D spending when there is faster obsolescence. Obsolescence does not systematically alter the procyclical timing of innovation: in faster-obsolescence industries, firms have little incentive to delay

[12] Concordance and support files available at http://www-2.rotman.utoronto.ca/~silverman/ipcsic/documentation_IPC-SIC_concordance.htm

[13] We inverted the variable by subtracting the value for each industry from 9.

implementation of innovations, so the timing of innovation mirrors the timing of R&D investment, and in slow-obsolescence industries, firms select when to introduce innovations to maximize rents, as a function of demand cycles and the threat of imitation.

Effective patent protection, allowing firms to capture the rents from innovation, provides a moderating influence on the strategic delay of innovation to match periods of high demand. When patents are more effective, firms have less incentive to delay innovation until higher-demand periods because the innovation can be introduced earlier and still capture profits during the subsequent high-demand period. Hence, we see evidence that innovation is less procyclical when patent protection is more effective at allowing firms to appropriate the gains from innovation.

One of the key insights Barlevy (2007) emphasized is that profit-maximizing firms will not shift R&D to take advantage of lower opportunity costs in downturns to the extent that it is socially optimal to do so. He theorized that this has the effect of making negative shocks more persistent than they would otherwise be and of making growth more costly to attain, because R&D investments are made at a time when the opportunity cost is higher. These effects combine to increase the welfare costs of macroeconomic shocks, and so Barlevy (2007) suggested that there may be a role for greater R&D subsidies in downturns to counteract the incentives to shift R&D to boom periods. Our results suggest that these subsidies might be targeted to the firms most likely to delay R&D investment: those in industries with faster rates of obsolescence. In addition, policies that strengthen intellectual property protection could reduce the strategic delay of innovations, potentially increasing consumption in periods of lower demand and facilitating growth and recovery.

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