How Does Innovative Activity Change as Industries Mature?

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Abstract

In this paper, we use evidence on the activity of U.S. publicly traded firms from the early 1980s to the mid-1990s to investigate whether innovation—measured by patenting activity—declines during the mature phase of the industry life cycle. Overall, the analysis reveals that the general level of patenting activity is not lower in mature industries than in emerging industries. We also find no evidence of a shift from product to process innovation with industry maturity, and no evidence that leaders innovate less in mature industries than in non-mature industries.

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Current theory emphasizes differences in how firms innovate across phases of the industry life cycle.[1] In this paper, we investigate empirically three important stylized assertions associated with the prevailing theory. The first assertion is that innovation is high during the early emergent stages of industries, but that it decreases over time as industries mature and decline.[2] The second is that innovation tends to be product-oriented during the emergent phase of industry development, but process-oriented during the maturity and decline phases.[3] The third is that industry leaders have less incentive to innovate during industry maturity than during the emerging and even the declining phases.[4]

To date there has been relatively little cross-sectional empirical analysis on these issues. One recent exception is Cohen and Klepper (1996), which shows that both large and small firms engage in significant product R&D while large firms engage in more process R&D.[5] Most empirical studies on innovation in industry maturity have focused on detailed intra-industry dynamics.[6] This paper contributes to panel-dataset literature that has been pursued in a relatively small number of prior studies (i.e., Gort and Klepper (1982)). We use data on a broad variety of industries to address whether the nature of innovative activity changes as industries mature. Our purpose is to examine whether the evidence supports the stylized assertions.

The setting for the study is the American economy between 1981 and 1997. Using data from the Dun & Bradstreet reports on business activity, we first identify mature industries based on net entry rates (following Klepper and Graddy (1990) and Gort and Klepper (1982)). The Dun & Bradstreet reports are helpful for identifying the inflection points that characterize the beginning and ending of maturity because they contain counts by industry of public corporations, private corporations, partnerships and proprietorships.

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[1] See Henderson and Clark (1990) and Tushman and O'Reilly (1997) for theoretical discussion on the association between industry phase and firm innovation. These and other authors have demonstrated that maturity and innovative activity are jointly determined. In this paper, we examine the association between firm behavior and industry maturity without stipulating whether a direction of causation between innovative activity and industry phase.

[2] Abernathy and Utterback (1978); Foster (1986).

[3] See Abernathy and Utterback (1978); Anderson and Tushman (1990); Cohen and Klepper (1996).

[4] Again, see Abernathy and Utterback (1978) and Cohen and Klepper (1996). Theorists often differ on their analysis of the reasons for why this shift occurs, but their research tends to support the idea that leaders become process-oriented in mature industries. For example, Reinganum (1983) points to the idea that industry leaders are more vulnerable to product innovation by smaller rivals either because of disincentives for innovation, while Henderson and Clark (1990) suggest that leaders may lack the organizational capabilities necessary for innovation.

[5] This finding supports the idea that industry leaders may engage in both product- and process-innovation as they seek to migrate their capabilities across technical generations. Easingwood (1988) points out that product life cycles may take very different forms than the cycles of the industries in which they are embedded.

[6] For example, see Henderson (1993) and Christensen (1997). Differing results across the industry studies confirm the theoretical prediction that innovative capabilities are contingent on industry structure and firm characteristics.

We then identify innovative activity using patent counts by industry. The source of data on patents is the United States Patent and Trademark Office. Patents have gained acceptance as proxies for technical advance. They are incomplete measures of innovation for several reasons, however. First, some firms are likely to patent their innovations because of their sizes and the nature of the underlying technology. In some situations, firms choose to keep their knowledge private by not patenting. Second, incentives for patenting may change over time as a firm's competitive environment develops. Our results must be interpreted cautiously because of these problems.

We associate patenting activity with particular industries using a concordance that relates patent classes to industries in which the patented technology is applicable (see Appendix 1). This concordance allows us to make inferences about the aggregate level of innovative activity associated with specific industries. We also use information on process and product patents to identify whether the nature of innovation differs in mature industries from non-mature industries. The results include information on differences by economic sector. Our study of industry leaders requires additional data from the Compustat Business-Segment and Basic files (both "active and "research" files) for 1981 to 1997, which we use to identify leaders. We then examine the tendencies of the leaders to generate patents using the US Patent and Trademark Office data.

Overall, the results do not conform to the first stylized assertion that innovative activity is lower in mature industries than in emerging industries. Although the relationship between industry maturity and innovation is somewhat sensitive to the rule for discerning maturity, we do find systematic evidence that innovation is not significantly lower in mature industries than in emerging industries. The results also do not support the second stylized assertion that innovation is more product-oriented in the emerging phase and more process-oriented in maturity and decline. Finally, our analysis shows that industry leaders engage in significant innovation during maturity, which refutes the assertion that leaders have less incentive to innovate during maturity than non-leaders. Furthermore, the absolute amount of innovative activity among leaders is not lower in mature industries than in emerging or declining industries. The leaders in mature industries tend to engage in diverse patenting activity outside their industries of leadership. In fact, the leaders in mature industries are significantly more diversified in their innovative activity than the leaders in non-mature industries, even when they are not diversified in their business activity. This finding provides a potential reconciliation with the third stylized theoretical assertion by allowing for the possibility of a decline in leader innovation in the mature industry.

The conclusion discusses a range of potential explanations for the findings. In particular, we suggest that industry leaders may continue to innovate in mature industries either because they seek options for migrating capabilities into new environments or because they intend to defend their positions. Overall, the results point to the need for theory characterizing how transitions out of maturity occur. Broadly, the evidence is consistent with the idea that industries may differ not only in their life cycles, but also in the pace and kind of change across technical trajectories.

Methods and Data

1. Identifying Mature Industries

The first methodological step involves the identification of industries in their mature phases. To make this identification, we use the Dun & Bradstreet Reports on American Business Activity from 1982 to 1995, which report on the years 1981 to 1994. These reports contain counts of all firms—private and public—operating in a specific SIC in each year. The reports are known for their comprehensiveness. In 1994, for example, D&B reported on 11.3 million businesses in 844 different industries.[7] Of the 844 industries tracked by Dun and Bradstreet, 516 have at least one patent assigned to them during the 1981-1994 period. We restrict our analysis to these 516 industries. Across the period, the average annual rate of growth in the number of enterprises was 10%.

We identify the date of industry maturity through three distinct algorithms consistent with prior research. In all three identification procedures, we examine rates of growth in the numbers of firms. Following Klepper & Graddy (1990) and Gort & Klepper (1982), our objective is to find the first date during the 1981-1994 period in which the growth in the number of enterprises reaches an inflection point. Gort & Klepper (1982) argue that the point of industry maturity occurs when the rate of *growth* in the number of firms begins to decline.[8] Identifying this point in practice is challenging because of short-term growth-rate volatility. To avoid spurious identification of the maturity date, our three algorithms are each based on changes in rolling averages over a multi-year period. All three algorithms incorporate a common rule that an industry hits maturity at the earliest date for which the number of firms grows at a rate less than some fraction of the growth rate in the prior period. The exact fraction differs across

[7] The D&B reports are distinguished from many other sources because they contain counts of privately held corporations, public corporations, international corporations, proprietorships, and partnerships in the U.S. by industry. The vast majority of businesses in the D&B dataset report sales below $5 million. The 844 industries exclude those associated with government agencies and those titled “not elsewhere classified” or “miscellaneous.”

[8] Note that this differs from the point at which the absolute *number* of firms declines. Typically the growth rate begins to decline well before the absolute number begins to decline. Note that the point of industry maturity also is likely to differ from the point of zero industry sales growth.

the algorithms. We consider an industry to be emerging prior to the point of maturity, and in decline at the earliest date at which the number of firms shrinks at some benchmark rate. The top two rows of Table 1 provide the precise definitions for each of our three algorithms.

2. Evaluating Innovation by Industry

The second step in the analysis involves identifying innovative activity by industry. Our measure of innovation is a count of the patents granted by the United States Patent and Trademark Office. While patent count represents an incomplete measure of a firm's technological assets—not all innovations are patentable and not all patentable innovations are patented—it has become accepted as a significant and objective proxy. The dataset consists of information on all patent applications between 1981 and 1994 that ultimately led to patent grants. We include information on patents assigned to all entities—including domestic and foreign firms, non-profit organizations, government bodies, and individuals—and not just patents granted to the leading firms within an industry. This feature of the dataset is important because it guarantees that our analysis covers innovative activity by both publicly traded firms and by the firms excluded from the Compustat dataset.

To evaluate the composition of innovative activity, we transform US patent-class assignments into industry assignments using the method reported in Silverman (1999). This method takes advantage of the Canadian Patent Office's (CPO) assignment of newly granted patents both to a patent class and to SIC categories. Using the Canadian information, we create a frequency distribution between the patent classes and four-digit SIC codes. This frequency distribution is used as a "transformation matrix" to determine the "patent-equivalent counts" by SIC code for the US patents (see the Appendix). This broad association of US patents with industries supports a finer assessment of industry innovation than possible in many prior studies, which have typically assumed that all patents assigned to a particular firm are related to that firm's primary SIC of operations (e.g., Ben-Zion 1984).

The Canadian classification system also supports a second kind of analysis of innovative activity by industry. When granting a patent, the Canadian examiners identify whether the patented innovation applies to a process or product. We use this information to calculate the proportion of Canadian patents that are process-related for each SIC and each year. We then adopt that assumption that this proportion is similar in the U.S. to examine the association between industry maturity and the proportion of innovation that is process-oriented.[9]

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[9] The analysis of process- and product-innovation differs from the evaluation of overall patenting in an important respect. For the analysis of process- and product- innovation, we rely exclusively on information about Canadian patenting activity. We have no way of mapping the process- and product-distinctions from the Canadian data into

3. Assessing the Roles of Industry Leaders

The third part of the analysis involves assessing the roles of industry leaders as innovators in mature industries.[10] To make this assessment, we use the Compustat Business-Segment Reports for 1981 to 1997 to identify the largest publicly-traded participant (based on sales) by year in each 4-digit SIC category. We then identify the patenting activity of each of the leaders using the data from the US Patents and Trademark Office.[11] Our purpose is to examine whether the industry leaders are more inclined than average toward innovative activity.

We also take advantage of information on leader identity by industry and year to explore whether leader turnover – measured as the unseating of one firm by another in terms of largest industry market share – is associated with changes in innovative activity. The results of this investigation are reported as a sensitivity analysis.

Empirical Results

1. Identifying Mature Industries

Table 1 summarizes the results on the classification of industries into life-cycle phases. The three algorithms differ in the criteria for identifying the point at which industry maturity begins. Algorithm 1compares three-year rolling averages in population growth to identify the beginning of industry maturity.[12] Algorithm 2 liberalizes the criteria slightly by also identifying maturity by declines in population numbers. Algorithm 3 tightens this criteria by examining five-year rolling periods rather than three-year periods.

The three algorithms identify between 401 and 475 industries out of the total of 516 industries as mature during some portion of the 1981-1994 period. Each of the algorithms shows a higher percentage of industries as mature in agriculture, manufacturing, wholesale trade, retail trade, and financial services than in business services, personal services, lodging, and entertainment services.

[TABLE 1 HERE]

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the US data except to simply assume that US industries are similar to Canadian industries. This assumption is flawed if Canadian industries are at different stages of development than their U.S. counterparts, and/or if patenting proclivities in Canada differ significantly from those in the U.S. This concern is partly mitigated by the fact that US firms account for more than 50% of the Canadian patents.

[10] We examined the innovative activity of only the leading firm in each industry rather than of multiple industry leaders. Our choice was motivated by the theoretical suggestion that a change in industry phase would affect the incentive for innovation at least for the leader.

[11] The matching process is imperfect because the US Patent and Trademark Office does not record firm cusip or ticker numbers. We therefore match the records using the company-name text field.

[12] The "sensitivity analysis" section at the end of the paper discusses the influence of additional criteria for identifying industry maturity.

There are also important differences across the algorithms in how industries are classified. Note that even the apparently small differences in the three algorithms lead to significant differences in phase classification. Between 286 and 402 industries are represented as “emerging” at some point during the period, and between 174 and 340 industries move out of maturity into the “declining” phase.[13] We imposed the criteria that an industry moves out of maturity and into decline when the absolute number of firms over any three-year rolling period is less than 97% of the number in the prior period.[14]

2. Evaluating Innovation by Industry

In this section we report the results of analysis on the first two of the stylized theoretical assertions. First, we evaluate whether innovative activity tends to be higher for industries in the emerging phases than for industries in the mature and declining phases. Table 2 shows the results.[15] For all three of our basic algorithms, patenting activity is as least as great in mature industries as in emerging industries. Under algorithm 1, innovation in mature industries is significantly greater in mature industries than in emerging industries. Under algorithms 2 and 3, innovation in mature industries is not significantly different than in emerging industries. The results are mixed on whether innovation is greater in mature industries than in declining industries. The findings show significantly lower levels of innovative activity in declining industries only under algorithm 1 but significantly higher levels in declining industries under both algorithms 2 and 3. This discrepancy is entirely due to activity in the business and services sector. Two industries, SICs 8062 (General Medical and Surgical Hospitals) and 8071 (Medical Laboratories), are classified as “declining” under algorithms 2 and 3 but not algorithm 1. If these industries were included as declining under algorithm 1, then it also would show a significantly higher level of innovation for declining industries than for mature industries.

[TABLE 2 HERE]

As a group, these results provide compelling evidence that innovative activity is not higher in emerging industries than in mature industries. They also suggest that innovation is not higher in mature industries than in declining industries. Thus, the first of the stylized assertions from the theory is refuted. The “sensitivity analysis”

[13] The figures for each phase sum to more than 516 because the typical industry passes through more than one phase during the period.
[14] See the “sensitivity analysis” section of the paper for a discussion of this criterion.
[15] Table 2 reports the aggregate amount of patenting without controlling for industry R&D expenditure. Thus, the results reflect the innovation level rather than innovative productivity. Other studies that account for R&D show that innovative productivity varies by industry (i.e., Cockburn and Griliches (1988)).

section of the paper demonstrates the robustness of these results and explains the rows in Table 2 labeled “Yale subset” and the columns in Table 2 labeled “Leader Change.”

[TABLE 3 HERE]

The second part of this section involves evaluating the stylized assertion that innovative activity is product-oriented in the emerging phase but process-oriented during the maturity and decline phases. Table 3 shows the percent of patents by industry, associated with processes rather than with products. For each of the three algorithms, the proportion of innovation that is process-oriented is at least as high in emerging industries as in mature industries. Process orientation is significantly lower in declining industries than in mature industries under two of the three algorithms. Thus, the results strongly refute the second stylized assertion. Overall, the results in Table 3 indicate that innovative activity takes on a different cast than suggested by industry-life-cycle (or S-curve) models.

3. Assessing the Roles of Industry Leaders

This section examines the third stylized assertion that industry leaders engage in less innovation during maturity than during other phases. This assertion is based partly on the idea that industry leaders have less incentive to innovate because innovation may encroach upon their established market positions.

The results in Table 4 describe the patenting activity of industry leaders. The first panel of the table describes the overall patenting activity of the leaders by industry phase. The second panel describes the patenting activity of the leaders in only the industries that they dominate. Because many leaders are diversified into multiple industries, the figures in the first panel are substantially larger in magnitude than those in the second panel. Indeed, this is one of the most important results of this analysis; namely, that industry leaders tend to engage in a diverse range of innovative activities outside the industries that they lead.

[TABLE 4 HERE]

It is important to clarify that this finding about leader innovation reflects the nature of the underlying dataset. Recall that the dataset incorporates information on the innovative activity of industry leaders regardless of the industry in which it occurs. The innovative activity of leaders in mature industries may reflect diversifying innovation in outside industries as well as reinvestment in the host industry. Leaders may be engaged in both diversification and reinvestment, perhaps to exploit economies of scope in research and development. In the following analysis, we separately identify innovative activity by leaders in their home industries and in other industries to isolate whether the activity is reinvestment or diversifying.

The figures at the bottom of each panel in Table 4 indicate that leaders in mature industries do not engage in significantly less innovative activity as leaders in emerging and declining industries. This result holds across all three algorithms for identifying industry maturity. Indeed, under algorithm 1, overall leader innovation in mature industries is significantly greater than in emerging industries. A comparison across the two panels reveals that this difference is significant because mature industry leaders are engaged in diversifying innovation, however. In the mature industries in which they dominate, the leaders engage in more innovation than their counterparts in emerging industries, but the difference is not significant.

Under algorithms 2 and 3, the results are similar. The leaders of mature industries appear to engage in as much innovative activity as their counterparts in emerging industries. Much of this activity is directed outside the mature industry itself. Even after accounting for this diversifying innovation, however, the leaders of the mature industries are no less engaged in innovative reinvestment than the leaders of emerging industries. The results on the difference between mature-industry leaders and declining-industry leaders are mixed, however. Under some algorithms, declining-industry leaders appear just as innovative as mature-industry leaders, although this result is not robust, and we therefore discount it. The principal result is that mature-industry leaders are just as innovative as emerging-industry leaders.

As a whole, these results debunk received theory that suggests a tendency for leaders to abandon innovative activity in mature settings. Leaders engage in extensive patenting, although much of this activity is relevant outside the industry of dominance. This result suggests that leaders engage in innovation that extends their positions into other settings. More research is needed to understand the structural relationships that may allow leaders to exploit economies of scope in innovative activity as their industries move through maturity.[16]

Sensitivity Analyses

We included a number of sensitivity analyses to verify the robustness of results.

Identifying Mature Industries. Our first set of sensitivities involved the process by which we identify industries as mature. Ideally, the data would support a replication of the classification mechanism in Klepper and Graddy (1990), in which industries are assigned into phases based on gross entry and gross exit rates.

Unfortunately, data on all the sectors of the American economy is not available for this kind of assessment. We therefore resorted to evaluating phases through examination of net entry rates in our main analysis.

A complication arose in the application of the criteria. Klepper and Graddy (1990) use five-and ten-year moving averages to identify the inflection point at the beginning of an industry's mature phase with an overall decline in population growth rates, and the inflection point at the ending of the mature phase with an overall decline in the absolute population. We could not apply the same five- and ten-year criteria because our panel consists of just 14 years of data. If we were to examine annual averages, then we would spuriously identify industries as moving between phases with intra-phase volatility in firm counts.[17] We therefore elected to use three- and five-year rolling averages. To eliminate the noisiness due to intra-phase volatility, we adjusted the criterion for identifying the beginning of industry maturity from the point of decline in population growth to the point at which population growth rates are less than 3%-5% of the prior period's rate. (Note that 3%-5% reflects real rates of overall business activity during the period.) If we had required an absolute decline in population growth rates, then the number of industries identified as mature would have been significantly lower. Similarly, we adjusted the criteria for identifying the ending of industry maturity by examining the point at which the population count declined to less than 97% of the prior period rather than to less than 100% of the prior period, as suggested by Klepper and Graddy (1990). Again, the purpose was to eliminate spurious identification due to general volatility.

We ran a number of sensitivities on each of these criteria to determine their robustness. The main results reported in the paper for the three algorithms broadly represent the range of findings from the sensitivities. In addition to algorithms 1, 2, and 3, we obtained results for three additional algorithms. In each case, the criteria for the beginning of industry maturity is adjusted to reflect either a 0%, 3%, or 5% threshold on population growth rates, or a 3- to 5-year rolling average. We find no material difference in the results on innovation from those reported for algorithms 1, 2 and 3 for all three of the supplementary analyses.

In a separate sensitivity analysis, we replicate the results after assigning each industry to just one phase for the entire period. Our purpose is to obtain a cross-sectional assessment that would not be at all sensitive to the points of transition between the different phases. For this analysis, industries are assigned to the longest of the phases with which they were associated under algorithm 1 of the main analysis. We then examine whether

[16] The results in Table 4 point to the possibility that these structural characteristics may differ substantially across sectors.

innovative activity is significantly different for the emerging, mature, and declining industries in a model that incorporates year and industry fixed effects.[18] The results indicate that patenting activity in mature industries is not significantly different than in either emerging or declining industries. When industries are assigned to the longest phases with which they were associated under algorithms 2 and 3, a significant does arise: patenting activity is lower in declining industries than in mature industries. Again, the results are consistent with our main findings.

In another sensitivity analysis on the phase assignments, we replicate the Klepper and Graddy criteria (1990) in a different way. For each industry, we define "stage 1" as all years up to the year with the largest population of firms during the 1981-1994 period. Stage 2 begins with the year of maximum population and continues until the first year t such that the population change between t and t+3 is less than 1% of the maximum population. Stage 3 begins with year t and continues to the end of the time period. We then replicate our main results regarding innovation by analyzing the aggregate amount of patenting activity by each phase under the assumptions of random-effects generalized least squares. Analysis both on manufacturers and on all sectors shows that patenting activity was significantly greater in stage 2 than in stage 1, and that patenting activity was not significantly lower in stage 2 than in stage 3. Thus, our main results are robust to this test.

<u>Evaluating Innovation by Industry.</u> The second set of sensitivity analyses addresses the robustness of our findings on innovative activity within industries. To determine whether our results are driven by inclusion of industries that typically eschew patenting, we replicate our analysis on a subset of industries for which patents are particularly important. Patent importance is determined by reference to the Yale study of innovation (Levin et al. 1987), which involved surveying several hundred R&D managers in 227 different industries (in 4-digit SICs 2 and 3) about the mechanisms their organizations used to appropriate returns from innovation. These mechanisms included the importance of patents for first protecting innovations from imitation and second generating royalty streams from licensing. The "Yale subset" in Table 2 reports results for only those industries rated above the mean in patent importance for each of the two questions. The subset includes 126 industries with either strong patent protection or royalty streams. The results at the bottom of Table 2 show higher overall patenting in the Yale subset, as expected. Even for the Yale subset, innovative activity is not significantly lower in mature industries than in

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[17] A preliminary evaluation suggested that this inadequate criterion would identify the average industry as cycling nearly three times through all three phases during the 14-year period.

[18] Specifically, we estimate Patent $\text{activity}_{it} = \beta_0 + \beta 1(\text{EMERGING}) + \beta_2(\text{DECLINING}_{it})$+ fixed effects(SIC) + fixed effects(Year) + e_{it} where EMERGING and DECLINING are each categorical variables that equal 1 if industry i is classified as an emerging, or declining industry, respectively, at time t.

emerging industries. Innovative activity is significantly lower in declining industries than in mature industries only under one algorithm and in one sector: agriculture and mining. As a whole, these results provide strong support for the basic conclusion that innovative activity is not lower in mature industries than in emerging industries. The results also support the idea that innovation may be as important in industry decline as in maturity.

The second sensitivity analysis on industry innovation involves a completely different mechanism for evaluating the inflection points in industry development. Instead of relying on distinctions between emerging, mature, and declining phases, this analysis considered industries as involved in either "change" or "no change" phases. "Change" phases were defined as periods in which the identity of the industry leader differed from the prior period. "No change" phases were those in which the identity of the leader stayed the same. This sensitivity analysis, also reported in Table 2, considers industries less as evolutionary systems and more as occasionally subjected to punctuated shifts, with punctuation marked by turnover in leadership. Even under this radically different perspective, the analysis shows no evidence of significantly less innovation during stable periods. Table 2 reports no significant difference in innovative activity during leadership change than in leadership stability.[19]

The third sensitivity analysis is a replication of the process- and product-patenting analysis in Table 3 on the Yale subset. The results are presented at the bottom of Table 3. The overall level of patenting for the Yale subset is significantly higher than for the population as a whole, as expected. The results conform closely to those for the broader population, and confirm the finding that patenting is not significantly more process-oriented during successive phases of the life cycle.

Conclusion

In this study, we investigate innovative activity in a broad variety of sectors. Using data from the Dun and Bradstreet Reports, the US Patent and Trademark Office, the Canadian patent-industry concordance, and the Compustat Business-Segment Reports, we test three stylized assertions that are prevalent in the literature. In particular, we find:

- No evidence of less innovative activity in mature industries than in emerging industries
- No evidence of more process innovation in mature industries than in emerging or declining industries
- No evidence that mature-industry leaders are less innovative than emerging-industry leaders, although mature-industry leaders engage in significant diversifying innovation as well as reinvesting innovation

[19] Of course, the direction of causality here is complex. Industry change may be caused by leadership innovation just as leadership innovation may be motivated by industry change.

The analysis points to the difficulty of establishing satisfactory algorithms for discerning the inflection points between the evolutionary phases of industry development. To deal with this difficulty, we use three distinct algorithms for our main analysis, and confirm our results through a series of sensitivity tests and robustness checks. The difficulties in the approach point to the need for further research on mechanisms for identifying inflection points without relying on a long retrospective time series.

As a whole, the results suggest that industry-life-cycle models based on the S-curve may not comprehensively describe innovative activity in mature industries. In particular, the results suggest that industries may be distinguished not by stage of maturity, but rather by the pace and kind of innovation. The analysis suggests that insight into innovative processes may arise not from the classification of industries into stages as defined by net entry rates, but rather from the classification of industries by the structural characteristics that drive the capability to adopt innovation. The study also points to the difficulty of implementing industry-life-cycle models in cross-sectional data. Rules for discerning industry phases must be accurate, but flexible enough to accommodate major differences in how evolution occurs in different contexts.

The main implication of the results is that industries may differ systematically in the ways in which technical trajectories overlap as well as in how dominant designs emerge. In some situations, product- and process-innovation by leaders may allow them to survive across generations. In other situations, leaders may be displaced despite significant innovative activity. Further work is needed to identify the structural conditions that support different models of industry evolution both within and across technical trajectories.

Appendix: Mapping Patents into Industries[20]

When the U.S. Patent and Trademark Office (UPSPTO) grants a patent application, the granting officer assigns the patent into a "patent class" using categories established as part of the U.S. Patent Classification (USPC) system. Currently, the system includes over 350 distinct categories. The granting officer also assigns the patent into a class under the International Patent Classification (IPC) system, which consists of a similar number of categories. Patent classes are defined by characteristics of the underlying technology rather than by industry characteristics. As a result, the classes cannot be easily identified with the industries defined by the SIC system (Scherer 1984). The lack of correspondence between USPC and SIC classes makes it difficult for researchers to associate patenting with the specific industries in which the patents are used. In the early 1980s, the Office of Technology Assessment and Forecasting (OTAF) developed a concordance linking USPC and SIC classes. However, this concordance is limited to just 57 categories, and the categories are aggregated at the 2- and 3-digit level. As a result, the OTAF concordance is insufficiently detailed for many research goals. Scholars have also criticized the OTAF concordance for the simplicity of its one-to-one correspondence between the USPC and SIC because patents may be used in more than one industry (Griliches 1990).

An ideal solution for researchers would be for the USPTO to assign SIC codes (in addition to a USPC code) to each patent. It is unlikely that the USPTO will revise its approach soon, however. In contrast, the

[20] This methodology is described in greater detail in chapter IV of Silverman (1996).

Canadian Patent Office (CPO) undertook such an effort between 1978 and 1994 (Ellis 1981). The CPO assigns each patent granted in Canada to its appropriate patent class, using the International Patent Classification (IPC) system rather than the USPC, and also assigns the patent to the appropriate 4-digit Canadian SIC of use.

Using the CPO database for 1978-1994 (which covered more than 200,000 patents), we calculate the frequency with which patents in each patent class were assigned to each SIC of use. We then use the resulting frequency distribution as a probability distribution to relate patent classes to SIC codes. For example, suppose the CPO granted 376 patents assigned to IPC class A01N between 1978 and 1987, and assigned these patents to SICs as follows:

SIC	#	%
3711	138	37
3712	81	22
3194	75	20
3799	34	9
etc.	…	…

Based on this frequency distributions, any single patent assigned to A01N during this time period has probability 0.37 of being assigned to SIC of Use 3711, 0.22 of being assigned to SIC 3712, etc. Under the assumption that like patents are assigned and exploited by similar processes in the U.S. and Canada, then the same probability distribution is relevant for patents assigned in the U.S. Using the probability distribution derived from the Canadian data, we can associate each patent issued in the U.S. to its corresponding probability-weighted SICs.

Ideally, the robustness of this procedure could be evaluated by comparing the results with the “true” assignment of a US patent to SIC categories. Of course, there is no comprehensive source of data on the “true” assignment of US patents to industries (or it would have been used directly to derive the frequency distribution). However, in the late 1970s, Scherer supervised a monumental project in which over 15,000 U.S. patents were individually assigned to a 3- or 4-digit SIC code. Scherer then evaluated the accuracy of the OTAF’s concordance by comparing its SIC assignments for 99 patents selected from the 15,000 in the Scherer study. The OTAF’s assignments matched Scherer’s at the 3-digit level for 50 of the 99 patents, and at the 2-digit level for 67 of the 99 patents. Silverman (1996) evaluated the accuracy of the Canadian-based concordance by replicating Scherer’s procedure using the same 99 patents. As reported therein, the Canadian-based concordance performed much better than the OTAF concordance. The Canadian-based concordance yielded up to 68 matches at the 4-digit level, 72 matches at the 3-digit level, and 90 matches at the 2-digit level. Thus, the best available test verifies the robustness of the approach.

The analysis proceeds with an application of the concordance to all granted U.S. patents with application dates between 1981 and 1994. For each year, we link all patents applied for in that year – regardless of the identity of the assignee – to the SICs of use. We then sum the total number of probability-weighted-patents to obtain a virtual “patent count” for each SIC. For example, if 1000 U.S. patents in IPC class A01N were applied for in 1981, then these would translate into 370 “probability-weighted patents” associated with SIC 3711 (1000 patents * 37%, based on the example above). At the same time, patents from several other IPCs may also map into SIC 3711 with varying degrees of frequency, so that the aggregate number of probability-weighted patents assigned to SIC 3711 will likely be much higher than 370. Our efforts result in a count of probability-weighted patents associated with each SIC in each year.

For industry leader patenting activity, we identify all patents assigned to each industry leader in each year of our study. We identify patents assigned to the parent company only, and not to subsidiaries. This may result in some underestimation of patenting activity by industry leaders, since some corporations assign some of their patents to subsidiaries rather than to the parent entity.

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Table 1: Breakdown of industries by stage, by sector

				Algorithm 1			Algorithm 2			Algorithm 3		
	Maturity defined as:			The first year in which the number of firms grows during a 3-year period at less than 3% of the growth rate in the prior 3-year period			The first year in which the number of firms declines over a 3-year period, or the number of firms grows during a 3-year period at less than 3% of the growth rate in the prior 3-year period			The first year in which the number of firms declines over a 5-year period, or the number of firms grows during a 5-year period at less than 3% of the growth rate in the prior 5-year period		
	Decline defined as:			The first year in which the number of firms during a 3-year period is less than 97% of the number in the prior 3-year period			The first year in which the number of firms during a 3-year period is less than 97% of the number in the prior 3-year period			The first year in which the number of firms during a 3-year period is less than 97% of the number in the prior 3-year period		
			Total	Emerge	Mature	Decline	Emerge	Mature	Decline	Emerge	Mature	Decline
0,1,2	Agriculture;	# industries [a]	211	165	165	143	120	189	73	101	154	53
	Mining	# industry-years		978	728	1002	415	1690	499	408	1381	326
3	Manufacture	# industries	214	172	172	145	124	205	112	137	183	86
		# industry-years		863	831	1182	333	1707	817	490	1477	582
4	Transportation	# industries	23	16	17	15	12	20	11	15	16	7
		# industry-years		83	85	97	46	138	72	65	113	35
5	Wholesale and	# industries	20	17	16	14	11	19	10	12	16	7
	Retail Trade	# industry-years		95	68	82	23	152	66	55	110	38
6	Financial Services	# industries	5	4	4	4	5	5	2	5	5	2
		# industry-years		29	15	20	22	39	9	26	35	9
7	Lodging;	# industries	28	20	19	16	9	26	17	11	23	15
	Entertainment	# industry-years		102	93	116	29	201	118	42	168	98
8	Business &	# industries	15	8	8	3	5	11	9	5	7	4
	Personal Svcs	# industry-years		46	61	26	13	60	81	24	42	32
	All industries	# industries	516	402	401	340	286	475	234	286	404	174
		# industry-years		2196	1881	2525	1881	3987	1662	1110	3226	1120

[a] # industries experiencing stage for at least one year between 1981 and 1994.

Table 2: Patenting activity by sector for mature vs. non-mature industries (standard errors in parentheses; * = significantly different from mature at p < 0.01)

		Algorithm 1 **(N = 8,406)**			**Algorithm 2** (N = 7, 053)			**Algorithm 3** (N = 7,053)			**Leader Change** (N = 7,053)	
SIC	Description	Mature	Emerging	Declining	Mature	Emerging	Declining	Mature	Emerging	Declining	No change	Change
0,1,2	Agriculture; Mining	78.9 (7.3)	57.7 (4.2)	57.4 (5.1)	84.2 (5.6)	70.5 (9.2)	**122.5 *** **(12.5)**	65.7 (4.2)	69.3 (8.8)	**167.0 *** **(18.6)**	100.8 (7.0)	154.3 (18.0)
3	Manufacture	314.4 (21.4)	**237.4 *** **(14.1)**	**211.7 *** **(16.4)**	246.0 (11.1)	238.5 (21.8)	**471.3 *** **(27.6)**	246.0 (13.0)	287.4 (19.2)	**391.3 *** **(31.5)**	343.0 (13.4)	395.4 (34.9)
4	Transportation	47.0 (5.7)	38.3 (5.4)	42.7 (5.8)	41.4 (4.6)	**21.4 *** **(6.0)**	51.8 (6.8)	53.9 (5.3)	34.0 (5.6)	58.3 (11.2)	45.3 (5.0)	25.2 (9.6)
5	Wholesale and Retail Trade	6.5 (1.4)	3.7 (0.8)	10.9 (2.6)	9.4 (1.5)	6.6 (2.9)	12.4 (3.0)	10.4 (2.0)	4.8 (1.2)	**3.2 *** **(0.3)**	11.9 (1.7)	6.8 (2.3)
6	Financial Services	0.6 (0.1)	**0.9 *** **(0.1)**	**0.3 *** **(0.1)**	0.7 (0.1)	1.0 (0.1)	**0.2 *** **(0.1)**	0.6 (0.1)	**1.1 *** **(0.1)**	**0.2 *** **(0.1)**	NA	NA
7	Lodging; Entertainment	26.9 (5.7)	24.9 (4.8)	25.9 (5.8)	25.0 (4.1)	61.1 (13.7)	**7.6 *** **(1.0)**	26.5 (4.6)	**4.0 *** **(0.8)**	**6.9 *** **(1.2)**	15.7 (3.2)	26.7 (9.7)
8	Business & Personal Svcs	693.6 (194.5)	318.1 (104.3)	277.3 (68.5)	189.7 (59.7)	61.4 (26.1)	564.1 (142.8)	191.6 (83.7)	32.0 (5.9)	**1210.6 *** **(328.3)**	582.3 (128.2)	327.9 (166.7)
	All industries	195.6 (12.2)	**128.4 *** **(6.6)**	**127.9 *** **(8.1)**	147.0 (5.6)	127.6 (9.8)	**299.2 *** **(16.4)**	142.5 (6.4)	155.4 (9.8)	**289.1 *** **(20.6)**	223.9 (5.4)	271.7 (20.5)
		Yale Subset (N = 2, 097)			**Yale Subset** (N = 1,749)			**Yale Subset** (N = 1,749)			**Yale Subset** (N = 1,195)	
0,1,2	Agriculture; Mining	230.9 (29.3)	158.5 (16.8)	**138.5 *** **(17.5)**	228.3 (19.3)	224.6 (39.9)	242.4 (45.3)	146.7 (13.3)	241.3 (41.1)	282.4 (52.9)	264.4 (28.7)	319.3 (39.6)
3	Manufacture	408.8 (39.8)	324.5 (28.5)	293.4 (39.8)	334.8 (23.0)	280.9 (61.6)	475.3 (57.3)	320.0 (26.0)	393.8 (36.5)	472.8 (320.0)	398.8 (29.7)	451.4 (43.3)

Table 3: Proportion of patents that are process patents, mature vs. non-mature industries, by sector (standard errors in parentheses* = significantly different from mature at p < 0.01)

		Algorithm 1 **(N = 8,406)**			Algorithm 2 **(N = 7,503)**			Algorithm 3 **(N = 7,503)**		
SIC	Description	Mature	Emerging	Declining	Mature	Emerging	Declining	Mature	Emerging	Declining
0,1,2	Agriculture;	14.4%	**18.0% ***	13.7%	16.7%	17.1%	**10.7% ***	17.4%	***17.7%***	**12.6% ***
	Mining	(0.7%)	**(0.7%)**	(0.7%)	(0.5%)	(0.9%)	**(0.6%)**	(0.6%)	(1.0%)	**(0.8%)**
3	Manufacture	10.4	11.4	**8.3 ***	10.2	11.2	**8.4 ***	10.1	11.2	8.9
		(0.4)	(0.5)	**(0.4)**	(0.3)	(0.7)	**(0.4)**	(0.3)	(0.6)	(0.5)
4	Transportation	11.2	8.0	11.0	9.0	**4.3 ***	13.4	11.7	8.3	11.2
		(1.4)	(1.0)	(1.8)	(0.9)	**(1.1)**	(1.6)	(1.2)	(1.2)	(2.4)
5	Wholesale and	1.4	0.9	0.7	1.3	**0.0 ***	0.6	0.8	1.5	1.2
	Retail Trade	(0.5)	(0.5)	(0.4)	(0.4)	**(0.0)**	(0.4)	(0.2)	(0.)	(0.8)
6	Financial Services	0.0	1.8	4.8	1.4	0.0	5.6	1.6	0.0	5.6
		(0.0)	(1.8)	(4.8)	(1.4)	(0.0)	(5.6)	(1.6)	(0.0)	(5.6)
7	Lodging;	2.6	**6.2 ***	1.5	3.1	**9.6 ***	3.3	2.8	4.5	4.1
	Entertainment	(0.6)	**(1.0)**	(0.6)	(0.6)	**(1.7)**	(0.7)	(0.6)	(1.5)	(0.9)
8	Business &	3.4	4.3	8.7	3.9	4.5	**6.8 ***	2.9	2.0	**7.5 ***
	Personal Svcs	(0.7)	(0.9)	(2.2)	(0.7)	(1.6)	**(0.9)**	(0.7)	(0.5)	**(1.5)**
	All industries	11.1	**13.5 ***	10.0	12.1	12.9	**8.6 ***	12.4	12.4	**9.4 ***
		(0.4)	**(0.4)**	(0.4)	(0.3)	(0.5)	**(0.3)**	(0.3)	(0.5)	**(0.4)**
		Yale Subset (N = 2,097)			**Yale Subset** (N = 1,749)			**Yale Subset** (N = 1,749)		
0,1,2	Agriculture;	22.6%	**29.5% ***	20.3%	26.3%	26.8%	**16.7% ***	26.3%	27.5%	**17.7% ***
	Mining	(1.6%)	**(1.5%)**	(1.5%)	(1.0)	(2.6%)	**(2.2%)**	(1.2%)	(2.9%)	**(2.5%)**
3	Manufacture	10.9	12.4	10.5	10.8	13.8	11.2	10.8	11.7	12.1
		(0.7)	(0.8)	(0.7)	(0.5)	(1.5)	(0.8)	(0.6)	(0.9)	(1.0)

Table 4: Leadership innovation patterns, by sector

	All patenting	Algorithm 1 **(N = 4,903)**			Algorithm 2 **(N = 4,052)**			Algorithm 3 **(N = 4,052)**		
SIC	Description	Mature	Emerging	Declining	Mature	Emerging	Declining	Mature	Emerging	Declining
0,1,2	Agriculture; Mining	27.4 (4.2)	20.3 (2.8)	26.9 (4.5)	34.5 (3.7)	**18.5 *** **(4.3)**	24.3 (4.2)	30.5 (4.0)	**14.5 *** **(2.9)**	32.1 (5.6)
3	Manufacture	82.8 (10.3)	56.0 (5.0)	55.5 (7.0)	58.3 (4.8)	53.4 (8.3)	77.1 (9.7)	58.0 (5.3)	63.1 (7.2)	72.4 (11.8)
4	Transportation	1.9 (0.8)	5.4 (1.7)	3.4 (0.9)	2.5 (0.7)	7.1 (2.2)	2.8 (1.2)	2.4 (0.7)	3.1 (1.4)	6.3 (2.5)
5	Wholesale and Retail Trade	1.3 (0.5)	1.5 (0.5)	0.5 (0.1)	1.2 (0.3)	0.8 (0.5)	0.7 (0.3)	1.1 (0.3)	1.6 (0.8)	1.1 (0.6)
6	Financial Services	NA	NA	NA	NA	NA	NA	NA	NA	NA
7	Lodging; Entertainment	0.3 (0.2)	4.6 (2.0)	0.2 (0.1)	3.0 (1.3)	0.0 (0.0)	0.2 (0.1)	4.3 (1.8)	0.1 (0.1)	0.3 (0.1)
8	Business & Personal Svcs	0.0 (0.0)	0.5 (0.4)	**59.8 *** **(16.8)**	5.2 (3.3)	1.2 (0.5)	11.5 (4.5)	1.4 (0.8)	0.1 (0.1)	3.7 (1.1)
	All industries	50.3 (5.3)	**34.1 *** **(2.6)**	39.6 (4.1)	42.3 (62.8)	32.7 (4.3)	49.2 (5.5)	41.1 (3.1)	37.6 (4.0)	49.9 (6.8)
	Patenting in primary SIC	Algorithm 1 **(N = 4,903)**			Algorithm 2 **(N = 4,052)**			Algorithm 3 **(N = 4,052)**		
0,1,2	Agriculture; Mining	3.5 (0.8)	1.7 (0.4)	0.9 * (0.2)	2.9 (0.5)	2.4 (0.8)	**1.1 *** **(0.3)**	1.6 (0.2)	0.8 (0.2)	1.5 (0.4)
3	Manufacture	9.3 (2.1)	5.9 (0.9)	4.0 (0.6)	4.8 (0.5)	3.5 (0.9)	7.9 (1.8)	4.6 (0.5)	**2.9 *** **(0.4)**	5.0 (1.0)
4	Transportation	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
5	Wholesale and Retail Trade	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
6	Financial Services	NA	NA	NA	NA	NA	NA	NA	NA	NA
7	Lodging; Entertainment	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
8	Business & Personal Svcs	0.0 (194.5)	0.0 (0.0)	0.4 (0.2)	0.1 (0.1)	0.0 (0.0)	0.1 (0.1)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	All industries	5.8 (1.1)	3.4 (0.4)	**2.4*** **(0.3)**	3.5 (0.3)	2.6 (0.2)	4.6 (1.0)	2.9 (0.3)	**1.7 *** **(0.2)**	3.2 (0.5)