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Measuring Firm Innovation and its Relationship with IPO and M&A Activities

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Abstract

This paper examines the changes in firms' innovation performance around initial public offerings (IPO) and mergers and acquisitions (M&A) using innovation data based on patent applications, new product introductions, and scientific article publications. The quantity of innovation is measured by number of innovative outputs and the quality of innovation is measured by a variety of metrics including patent or article citation count and content-based novelty score. Results generally show that innovation quantity increases while innovation quality declines following IPO and M&A events. The findings are consistent among patent-based, product-based, and publication-based metrics, and confirm with the results from previous literature. In addition, innovation performance is found to vary with financial performance and industry characteristics. Firms that exhibit larger asset and cash holdings, higher profitability, and more R&D investments are in general more innovative in terms of both quality and quantity. In post-IPO or post-M&A years, higher industry sales concentration and geographic concentration tend to correlate with lower innovation quantity and higher innovation quality. This paper also attempts to study the mobility of innovative employees around IPO and M&A, but the results lack sufficient insights on whether the observed post-event decline in innovation quality can be explained by changes in the composition of innovators. Overall, despite the ability to produce more innovations after going public or acquiring another company, firms should be mindful of the potential loss in innovation quality.

Keywords

innovation, IPO, M&A, industry characteristics, financial performance, innovator mobility

Disciplines

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MEASURING FIRM INNOVATION AND ITS RELATIONSHIP WITH IPO AND M&A ACTIVITIES

By

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Table of Contents

Abstract

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Keywords: innovation, IPO, M&A, industry characteristics, financial performance, innovator mobility

1. Introduction and Literature Review

The quality of innovation is essential to a firm's long-term performance, as innovative activities can not only enhance a firm's competitiveness in the market, but also generate positive externalities for the society through the introduction of new technologies. According to the U.S. Department of Commerce (2007), innovation is "the design, invention, development and/or implementation of new or altered products, services, processes, systems, organizational structures, or business models for the purpose of creating new value for customers and financial returns for the firm." In other words, innovation needs to be both novel and commercially valuable. Literature on firm innovation has suggested that innovation capability is the most important determinant of firm performance and that higher innovativeness is related to better firm performance in terms of return on investment and profitability (Calantone, Cavusgil, and Zhao 2002). Despite the importance of innovation to corporate performance, it is oftentimes difficult for firms to maintain innovation capability over time, especially after firms experience substantial strategic changes such as initial public offerings (IPO) and mergers and acquisitions (M&A). It is likely that IPO and M&A events will impact a firm's innovation strategy and thereafter lead to changes in innovation performance.

There has been a large amount of research that investigates how general firm performance changes around IPO and M&A. Studies have shown that there is significant post-IPO deterioration in firms' operational and financial performance (Jain and Kini 1994). On the M&A side, mixed views have emerged on whether post-M&A performance of the combined firm improves or declines, with some scholars finding that long-term operational and financial performance of M&A activities depend on various factors such as size of the target firm and incentive compensation plans (Ramaswamy and Waegelein 2003).

It wasn't until recently that researchers have started to specifically link innovation, the most crucial driver of firm performance, with IPO and M&A events. While firms invest in innovation primarily through research and development (R&D) expenditures, many scholars have illustrated that R&D is not a reliable measure of innovation, as R&D only captures one observable input of innovation and does not account for other observable and unobservable aspects such as talent allocation and incentive compensation plans (He and Tian 2013). The most popular measure of innovation among scholars is patent information. Patent-based metrics are found to be more economically meaningful than R&D as they not only convey the strength of a firm's intellectual property but also provide insights into the firm's market value (Hall, Jaffe, and Trajtenberg 2005; Bernstein 2015). Scholars who utilize patent data in general find that the quality of innovation, as measured by the number of patent citations, tends to decrease following IPO activities due to short-termism – the pressures from shareholders to increase short-term earnings (Bernstein 2015; He and Tian 2013). In terms of innovation strategy, private firms tend to be more exploratory and rely more on existing knowledge while public firms are more exploitative and more likely to invest in new technologies (Gao, Hsu, and Li 2018). In terms of M&A, scholars have also applied patent-based metrics to explore the relationship between innovative activities and M&A considerations and discovered that post-merger innovation performance increases when there is a reasonable pre-M&A overlap between the technologies of the acquirer firm and those of the target firm (Bena and Li 2014; Cloodt, Hagedoorn, and Kranenburg 2006). One study also concludes that the quality of firm innovation is highest under private ownership, intermediate under M&A, and lowest under public ownership, based on patent data of VC-backed biotech firms (Aggarwal and Hsu 2013).

While there is already a moderate amount of research on the relationship between innovation performance and strategic activities in recent years, most of existing literature uses patent data as a proxy for innovation. Although scholars have illustrated the reliability of patent-based measurement of innovation (Hall, Jaffe, and Trajtenberg 2005; Bernstein 2015), this practice may still lack sufficient content validity as patenting is only one way to create innovation. Firms may also choose to innovate through academic publications, new product introductions, as well as other activities that are not patented or have not been patented yet. Several studies have adopted measures other than patent data to analyze firm innovation performance. Murray and Stern (2007) discover that innovation leads to both scientific publications and patent grants, with publications pre-dating patent grants and publication citations declining following patent grants. Moreover, Wies and Moorman (2015) measure firm innovation using new product introductions and find that public firms in the consumer-packaged goods industry show increased innovation level but decreased innovation riskiness compared to private firms. Despite the variety of innovation measures, application of simply one particular metric may still fail to provide a comprehensive image of a firm's innovation performance.

In addition to the lack of content validity in selecting proxy for innovation, most of the existing research also takes a very broad approach to assess innovation performance, which speaks to quantity of innovation and quality of innovation. While quantity can be measured in a straightforward way through counting the number of innovation outputs, the quality or degree of novelty of each innovation is harder to operationalize. The existing literature has largely used the number of citations a patent receives to measure innovation quality. According to Bernstein (2015), the citation count metric is capable of distinguishing between breakthrough innovation and incremental innovation as it reflects the importance other inventors place on the particular patent. However, citation count may not provide sufficient criterion validity since this metric only reflects the number of times an innovation is cited without looking into the specific content of the innovation output. It is possible that inventors from other firms are not citing the core idea in the patent, or that the patent is contributing an incremental idea to an existing field rather than putting forward a breakthrough idea.

2. Research Question and Hypotheses

This paper aims to contribute to existing literature on firm-level innovation performance and how it relates to strategic decisions. I intend to address the lack of content and criterion validity in innovation measurement by examining various innovation modes and innovation metrics to present a more thorough analysis of firm innovation performance. I study three modes of innovation – patent applications, new product introductions, and scientific publications – and explore how each innovation mode relates to IPO and/or M&A activities. When selecting metrics to measure the quantity and quality of innovation, in addition to the traditional metrics such as number of innovation outputs and number of citations, I also use other metrics that are derived from the specific content of each innovation output. Text mining of innovative content should allow for a more in-depth examination of innovation quality than simply counting the number of citations. For example, in analyzing scientific publications data, I assign an innovation novelty score for each published scientific article through calculating the average age of non-stop words in the abstract of the article.

This paper also attempts to explore possible reasons behind changes in innovation performance around IPO and M&A activities. While shareholder pressure for short-term earnings is widely regarded by the literature as a key reason for lower innovation quality of public firms (Bernstein 2015; He and Tian 2013; Asker, Farre-Mensa, and Ljungqvist 2014), innovator mobility may also explain this phenomenon as innovators are the main employees responsible for producing innovation output and they may leave or stay following the firm's strategic initiatives due to changes in organizational culture and incentive compensation plans (Bernstein 2015). This paper focuses on exploring the mobility of scientific publication authors around IPO and M&A activities. Additionally, innovation dynamics can also vary across industries due to the impact of different structural forces and differ across firms that exhibit distinct levels of financial performance. Thus, industry characteristics (sales concentration, turbulence or instability, geographic concentration) and financial metrics (total assets, net income, cash, R&D investments) are also examined as potential factors that may affect innovation performance around strategic activities.

3. Datasets

There are two pillars of data used in this paper. The first pillar includes data on firm-level innovative activities. Three categories of innovation data will be examined: patent applications, new product introductions, and scientific publications. The second pillar of data in the paper is firm-level strategic and financial information, including IPO and M&A dates and financial metrics.

A. Patent Data

Raw patent data is obtained from the patent database of the National Bureau of Economic Research (NBER), which contains more than three million patents filed to the United States

Patent and Trademark Office (USPTO) from 1976 to 2006 (Hall, Jaffe, and Trajtenberg 2001). The database is publicly available and includes the patents filed by each firm to USPTO as well as the number of citations, originality metric, and generality metric of each patent. The NBER database also contains matching of firm names in the USPTO database with GVKEY (a unique firm identifier) used by the Compustat financial information database so that I can match each firm's patent applications with its IPO status and other financial metrics.

B. Product Introductions Data

Data for new product introductions is gathered from the FactSet Revere database available on Wharton Research Data Services (WRDS). The dataset houses information on new product launches of all firms covered by FactSet since 2003. In addition to the dates of the firms' product launches, the database also contains each product's sector description as well as CUSIP firm identifiers for matching to the Compustat database.

C. Scientific Publications Data

Data for scientific publications is obtained from the Elsevier's Scopus database, which is the largest abstract and citation database of peer-reviewed literature. For each firm in my patent universe that is also included by Scopus, I collect basic publication information, such as topic and year, citation frequency, and author affiliations, as well as full abstracts of all articles published by the firm. Because Scopus does not contain unique identifiers for firm names, I input firm names into Scopus' web search query to download basic publication information and then match the firm names in the downloaded data to GVKEY identifiers. Article abstracts are downloaded from a combination of Scopus web searches and Scopus Abstract Retrieval API. I use PyScopus, a Python wrapper for Scopus API developed by Zuo, Zhao, and Eichmann (2017), and employ the Abstract Retrieval API to obtain abstracts by Scopus ID, which is a unique article identifier.

For both product introductions and scientific publications data, I focus on firms that overlap with my patent universe so that I can compare the analytical results from product-based and publication-based metrics with those from patent-based metrics.

D. Firm-Level Strategic and Financial Information

Most of the data on firm-level strategic and financial information comes from the Compustat North America database available on WRDS. Compustat contains U.S. and Canadian fundamental information of both active and inactive publicly-traded companies since 1950. For IPO events, I gather data items including IPO year, industry classification, and financial metrics of all firms in my universe from Compustat. Industry classification is indicated by the Standard Industry Classification (SIC) code which is a widely-used system for classifying firms into industry areas. Firm financial metrics include natural logarithm of total assets (Log Total Assets), ratio of R&D to total assets (R&D / Total Assets), ratio of net income to total assets (Net Income / Total Assets), and ratio of cash to total assets (Cash / Total Assets). Then, I combine data from each of the three innovation categories with IPO years, industry codes, and financial metrics.

For M&A events, I use the Thomson Reuters SDC database on WRDS which houses information on M&A transactions of public firms since 1965. To construct a relevant sample of M&A transactions, I follow the sample selection treatment by Bena and Li (2014). I include an M&A transaction only if the acquirer is seeking to own more than 50% of the target firm and owns at least 90% of the target firm after deal completion. In addition, the target firm's total assets must be valued at more than $1 million and neither the acquirer nor the target firm is a financial institution. Then, I combine data from each innovation category with M&A years, industry codes, and financial metrics.

4. Research Methodology and Results

My analysis mainly consists of two parts. I first run a series of Ordinary Least Squares (OLS) linear regression analyses on the relationship between innovation performance and IPO or M&A status based on patent data, product introductions data, and scientific publications data, respectively. Following Bernstein (2015), I consider innovation performance from three years before (-3) to five years after (+5) IPO or M&A events. I also control for industry characteristics and financial metrics that may relate to change in innovation performance around IPO and M&A events. The variables for industry characteristics include sales concentration, market turbulence, and geographic concentration, and the variables for financial metrics include natural logarithm of total assets, ratio of R&D to total assets, ratio of net income to total assets, and ratio of cash to total assets. After examining the relationship between innovation performance and IPO or M&A status, I explore innovator mobility around IPO and M&A activities based on author information of firms' scientific publications in order to analyze whether innovator mobility could be a potential reason for the observed innovation changes around strategic events.

A. Changes in Innovation around IPO and M&A Events

i. Changes in innovation around IPO based on patent metrics

Following Bernstein (2015), I first explore the relationship between patent-based innovation metrics and IPO activities. **Table 1** in the Appendix shows summary statistics for the patent applications of firms from three years before to five years after IPO events. My dataset includes 2,409 firms and 90,338 patent-firm-year observations. Patent applications are concentrated in Computers and Communication, Drugs and Medicine, and Electronics industries. Moreover, the mean number of patents increased for firms after they went public, but the mean number of citations decreased. This seems to confirm with Bernstein (2015) that firms engaged in higher number of innovations after IPO but the quality of innovation decreases.

For dependent variables, I use various patent-based metrics for innovation performance. Innovation quantity is measured by patent count (number of patents of each firm). Innovation quality is measured in three ways: citation count (number of times each patent is cited), generality (degree to which a patent is cited by patents from a more diverse range of technology classes), and originality (degree to which a patent is citing a broader set of technology classes). In order to mitigate skewness in the distribution of patent and citation counts, we use the natural logarithm of patent counts and the natural logarithm of citations counts. To avoid any zero values, I add one to the patent count or citation count when taking the natural logarithm.

The primary independent variable is IPO status, which is a dummy variable that goes from -3 to +5, representing 3 years before to 5 years after an IPO event. The coefficients for the dummy variables are with respect to the year of IPO (year 0). I also include industry sales concentration, industry turbulence, and industry geographic concentration which may also relate to innovation performance. Industry sales concentration is measured by the Herfindahl-

Hirschman index (HHI), which is the sum of squared market shares of all firms in an industry in a year. In order to ensure that my industry classification is neither too broad nor too narrow in the calculation of HHI, I use three-digit SIC codes. The universe of an entire industry is the set of all firms belonging to the three-digit SIC code classification in the Compustat North America database. In order to calculate the total sales of each three-digit-SIC industry in a specific year, I ignore differences between fiscal year and calendar year and assume that each firm generated the reported sales amount in the calendar year. Industry turbulence is calculated according to Matraves and Rondi (2007), who measure the instability of the market share of the top five firms in each industry over time. Geographic concentration of an industry is calculated using the EGI index based on Dumais, Ellison, and Glaeser (2002) who measure the degree to which an industry is geographically concentrated based on the state-level location of firms in the industry. While Dumais, Ellison, and Glaeser (2002) measure industry market share using employment data, I substitute sales revenue for employment. The formulas for the calculation of the three industry metrics are as follows.

$HHI = \sum_{i=1}^{N} s_i^2$, where s_i is the sales market share of firm i in the three-digit-SIC industry and N is the total number of firms within that industry.

$Turbulence = 1 - \frac{O_{t+1}}{N_{t+1}}$. I first identify the top 5 firms in each industry in terms of sales revenue at time t, then O_{t+1} is the cumulative squared market shares of the same old 5 firms at time $t+1$, and N_{t+1} is the cumulative squared market shares of the actual top 5 firms at time $t+1$.

$EGI = \frac{G_{it}/(1-\sum_s s_{st}^2)-HHI}{1-HHI}$, where s_{ist} is the share of industry i's time t sales in state s; s_{st} is the state's share of sales in the average industry; G_{it} is the sum of squared deviations of s_{ist} from s_{st}; and HHI is the Herfindahl-Hirschman index.

In addition to industry characteristics, I also incorporate firm financial metrics, including natural logarithm of total assets (Log Total Assets), ratio of R&D to total assets (R&D / Total Assets), ratio of net income to total assets (Net Income / Total Assets), and ratio of cash to total assets (Cash / Total Assets).

Based on these dependent and independent variables, I conduct regression analyses with firm and year fixed effects to study how patent-based metrics evolve from -3 to +5 years around IPO events. As such, the OLS equation I use is as follows:

$$\begin{aligned} Y_i = \beta_0 + \sum_{n=1}^{8} \beta_n IPO\_Status_i + \beta_9 HHI_i + \beta_{10} Turbulence_i + \beta_{11} EGI_i \\ + \beta_{12} Log\_total\_assets_i + \beta_{13} Net\_income\_to\_total\_assets_i \\ + \beta_{14} Cash\_to\_total\_assets_i + \beta_{15} R\&D\_to\_total\_assets_i \\ + \beta_{16}(IPO_i^{Post} * HHI_i) + \beta_{17}(IPO_i^{Post} * Turbulence_i) \\ + \beta_{18}(IPO_i^{Post} * Turbulence_i) + \varepsilon_i \end{aligned}$$

Y represents the innovation performance metric, and IPO_Status is a dummy variable showing the firm's status with respect to its IPO year ($IPO - 3$ means the firm is three years ahead of its IPO year). IPO_i^{Post} is equal to 1 if the firm is already past its IPO year, and

$IPO_i^{Post} * HHI_i$ represents the interaction between HHI and post-IPO status. The same notation applies to $IPO_i^{Post} * Turbulence_i$ and $IPO_i^{Post} * EGI_i$.

Results:

Table 2 of the Appendix shows my analysis on the firm-level change in patent count around IPO events, and **Table 3** shows the firm-level change in three patent quality metrics – average citation count, average generality, and average originality. As shown in Columns (1) and (2) of **Table 2** and Column (1) of **Table 3**, innovation in post-IPO years is characterized by significantly higher quantity of patents produced but significantly lower citation count. Nevertheless, as shown in Columns (2) and (3) of **Table 3**, most of the coefficients for generality and originality metrics are not statistically significant, and the coefficient values do not show a consistent pattern as the firm goes from private to public status. In terms of industry characteristics, I observe that in post-IPO status, industry sales concentration, turbulence, and geographic concentration are in general negatively related to patent count while positively related to patent quality metrics.

In addition, as shown in Column (3) of **Table 2**, I also conduct another regression analysis on patent count by adding four financial metrics variables: natural log of total assets, ratio of net income to total assets, ratio of cash to total assets, and ratio of R&D expenditure to total assets. The addition of these four independent variables to the regression disrupts the increasing trend on patent count with respect to IPO status. Nevertheless, the results suggest that firms with higher total assets, higher cash relative to assets, and higher R&D expenditure relative to assets tend to produce more innovation outputs. This corresponds to the common consensus that firms with more resources tend to have more capacity for innovation.

ii. Changes in innovation around M&A based on patent metrics

Next, I proceed to analyze the change in innovation performance around M&A events. I have only considered the innovation performance of acquirer firms, as most target firms would disappear following an acquisition. However, some target firms may remain as separate subsidiaries of their corresponding acquirer firms after acquisitions, so some patents may be assigned to the target firm rather than to the acquirer firm, despite the fact that the innovation comes from the acquirer firm as a whole. As such, this analysis may underestimate the innovation output following M&A events. Nevertheless, simply adding the patents assigned to post-acquisition target firms to the patent set of the parent firms would not work as the Thomson SDC database only contains M&A transactions involving public firms. Some public parent firms may have acquired private subsidiary firms that operate as a standalone entity in the US patent system and do not show up in the patent database.

My patent-M&A dataset contains 1,462 firms, 2,841 unique M&A transactions, and 473,023 unique patents. **Table 4** in the Appendix exhibits summary statistics of patent applications from three years before to five years after M&A transactions. Similar to the patent-IPO dataset, the Computer and Electronics sectors appear to have the greatest number of patents. In addition, the mean number of patents increases in post-M&A years, although the patent count data seem to be highly skewed. On the other hand, the average number of patent citations decreases following M&A.

Results:

I conduct regression analyses with firm and year fixed effects to study how patent-based metrics evolve from -3 to +5 years with respect to M&A events. **Table 5** of the Appendix shows the change in patent count around M&A events of acquirer firms, and **Table 6** shows the change in three patent quality metrics – average citation count, average generality, and average originality. I obtain similar results as in the IPO case. Innovation in post-M&A years for acquirer firms is characterized by higher quantity of patents produced (not significant) but significantly lower citation count. In post-M&A years, industry sales concentration is in general negatively related to patent count and positively related to patent quality metrics. Moreover, as observed in Column (3) of **Table 5**, higher values of total assets, cash capacity, and R&D expenditure correspond significantly to higher patent count.

iii. Changes in innovation around M&A based on product introduction metrics

Using the same method as in the patent case, I explore the relationship between changes in innovation performance and strategic activities based on the product introductions of firms. Because the FactSet Revere database primarily covers public firms, there is very limited data on the product introductions in the years before the firms went public. As a result, the analysis on the innovation changes from three years before to five years after IPO is not robust enough. I have decided to remove the analysis on product introductions for the case of IPO.

Table 7 in the Appendix displays summary statistics of the product introductions of firms from three years before to five years after M&A events. The dataset contains 1,222 firms, 2,652 unique M&A deals, and 72,687 unique product launches. Product launches are concentrated in Technology, Healthcare, and Consumer sectors. In addition, I observe that the average number of total product introductions is higher while the average number of breakthrough introductions is lower during the five years after M&A than during the three years before M&A.

The dependent variable for the quantity of product-based innovation is total product count (number of product launches). Since there is no equivalent of citation count for product launches, I follow Wies and Moorman (2015) to calculate breakthrough product count in order to measure the quality of product innovation. Since the FactSet Revere product database includes sector specification of each product, I have assigned each product launch to either breakthrough (product belonging to a new sector which the associated firm has never been in before) or reuse (product belonging to a sector that applies to previous products of the associated firm). As a result, the breakthrough product count is the number of breakthrough innovations by a firm each year, effectively acting as a measure of innovation quality. Similar to the analysis of patent-based metrics, the primary independent variable is M&A status (-3 to +5 years with respect to M&A events). Industry metrics and financial metrics are also included as controlling variables. Then, I run OLS linear regression analyses on the product introduction metrics against the independent and control variables with firm and year fixed effects.

Results:

Table 8 of the Appendix shows the changes in number of product introductions around M&A events. My results in general confirm with those derived from patent data. The coefficients for total product innovation in post-M&A years are generally not significant, but the coefficient values tend to be larger for post-M&A years, suggesting higher quantity of innovation compared to pre-M&A years. The change in breakthrough or novel innovation around M&A is shown in **Table 9**. The coefficient values for M&A status show a decreasing trend from three years before to five years after M&A, suggesting that the number of breakthrough innovations is significantly lower post-M&A compared to pre-M&A years. Therefore, this analysis confirms with patent-based results that innovation quantity tends to increase while quality tends to decline following M&A events.

In addition, higher total assets and higher R&D expenditure relative to assets are associated with higher number of product introductions, suggesting that firms with more resources and more R&D investments tend to produce more innovations. In post-M&A years, all of the three industry metrics (sales concentration, turbulence, and geographic concentration) are in general negatively related to both total product introductions and breakthrough introductions.

iv. Changes in innovation around IPO based on scientific publication metrics

In this section, I explore the relationship between innovation performance and strategic activities based on the scientific publications of firms. For dependent variables, innovation quantity is measured by article count (number of articles published by a firm in a year), and innovation quality is measured in two ways – citation count (number of times each article is cited) and novelty score.

The novelty score is calculated based on text mining of the abstract of each published scientific article. Following Wu, Lou, and Hitt (2019), I employ a bag-of-words model to identify non-stop words in the abstract of each article and calculate the age of each word by journal field. I first clean up my collection of words by removing punctuations, numbers, and stop words identified from the SMART stop-word list built into R's text mining package. I then reduce my "bag" so that it only includes the words appearing at least 1% of the time. **Table 10** shows summary charts from text mining of the abstracts.

To calculate word age, I follow the method of Wu, Lou, and Hitt (2019) and define that a word has an age of zero on its first appearance in a particular journal field. If a word has appeared previously, then the word age is the difference between application date of the article and the time the word first appears. Based on the bag-of-word model, an article's novelty score would be based on the average age of all non-stop words in the abstract. In order to avoid cases in which the age is zero, I add one to the age value. To obtain the novelty score of each article, I calculate the reciprocal of the scaled age of all non-stop words in the abstract and take the average of the reciprocal values as shown below. A firm's novelty score is the average score of the entire set of its published articles in a given year.

$$Novelty = \frac{1}{N}\sum_{w=1}^{N}\frac{1}{Age_w + 1}$$

Table 11 shows the summary statistics of scientific publications of firms from three years before to five years after IPO events. My dataset contains 786 unique firms and 6,603 unique publications (2,135 with abstracts available). The publications are concentrated in Biology, Engineering, and Medicine fields. The average publication count in post-IPO years is higher than in pre-IPO years, while both the citation count and the abstract novelty score in post-IPO years are lower than the pre-IPO case.

The primary independent variable is IPO status, which is a dummy variable that goes from -3 to +5, representing 3 years before to 5 years after an IPO event. Industry and financial metrics are also included as controlling variables. Then, I run OLS linear regression analyses on the scientific publication metrics against the independent variables with firm and year fixed effects.

Results:

As shown in **Table 12**, innovation quantity (as measured by number of scientific article publications) in post-IPO years tends to be higher than in pre-IPO years, suggesting higher quantity of innovation post-IPO. **Table 13** exhibits the change in the number of research collaborators, or article co-authors, around IPO and shows that the number of collaborators is significantly higher in post-IPO years than in pre-IPO years. This indicates that the increase in innovation quantity following an IPO process might be partially due to the increase in access to research collaborators and resources for firms.

To examine the quality of innovation, I first look at the change in article citation count around IPO. As shown in **Table 14**, however, this analysis does not generate significant results, and the coefficient values from three years before to five years after IPO do not show a consistent pattern. In order to better examine innovation quality, I use the novelty score calculated from text mining of the abstracts of each article. **Table 15** exhibits the change in firm-level average novelty score around IPO. Similar to the citation count analysis based on patent data, the novelty scores in post-IPO years are significantly lower than those in pre-IPO years. In addition, in post-IPO status, industry metrics including sales concentration, turbulence, and geographic concentration correlate positively with the novelty score, although the coefficients lack significance.

v. Changes in innovation around M&A based on scientific publication metrics

I repeat the publication-based OLS regression analysis for the M&A case. The dependent variables include publication count, collaborator count, average citation count, and average novelty score. The primary independent variable is M&A status, which is a dummy variable that goes from -3 to +5, representing 3 years before to 5 years after an M&A event. Industry and financial metrics are also included as controlling variables.

My publication-M&A dataset contains 267 firms, 488 unique M&A transactions, and 5,215 unique publications (3,797 with abstracts available). **Table 16** in the Appendix exhibits summary statistics of scientific publications from three years before to five years after M&A transactions. The Biology, Engineering, and Computer Science sectors appear to have the greatest number of publications. In addition, the mean number of published articles is higher in post-M&A years compared to pre-M&A years. While the mean novelty score decreases in post-M&A years, the average number of publication citations increases following M&A.

Results:

As shown in **Table 17**, results for innovation quantity (as measured by number of publications) are not significant but coefficient values do point to higher publication count in post-M&A years. Similar to the IPO case, firms tend to have more research collaborators post-M&A, as exhibited in **Table 18**.

I then proceed to analyze the change in article citation count around M&A and the regression results are shown in **Table 19**. Contrary to previous findings on innovation quality measured by citation count, the coefficient values for the average citation point to higher innovation quality in post-M&A years, although most results are insignificant. Nevertheless, when the abstract novelty score is examined in **Table 20**, I find that the novelty score decreases following M&A transactions, and this is consistent with previous findings that innovation quality declines post-M&A. In addition, industry sales concentration and geographic concentration have significantly positive correlations with the novelty score in post-M&A status. All four financial metrics, including log total assets, net income to total assets, cash to total assets, R&D to total assets correlate positively with the novelty score despite the coefficients lacking significance, suggesting that firms with more competent resources, deployable capital, and R&D investments may show higher innovation quality.

B. Innovator Mobility around IPO and M&A Events

The series of OLS regression analysis discussed in part A generally show that innovation quantity increases while innovation quality decreases following IPO and M&A activities. The findings are consistent among patent-based, product-based, and publication-based metrics. In order to explain why innovation performance experiences these observed changes around IPO and M&A activities, I focus on analyzing innovator mobility as a potential reason. According to Bernstein (2015), key inventors may choose to leave or stay following an IPO or M&A event due to changes in organizational culture and incentive compensation plans.

Following Bernstein (2015) who analyzes innovator mobility based on patent data, I utilize the Scopus database to examine the mobility of the authors of firms' scientific publications. Since Scopus provides unique author identifiers, the authors can be classified into three types. A “stayer” is defined as an author with at least a single paper before and after the IPO/M&A at the same firm; a “leaver” is defined as an author with at least a single paper at a sample firm before the IPO/M&A, and at least a single paper in a different company after the IPO/M&A; and a newcomer is defined as an author that has at least a single paper after the IPO/M&A event at a sample firm, but no papers before, and has at least a single paper at a different firm before the event. I attribute a publication equally to each author of the paper and compare the behavior of stayers, leavers, and newcomers from 3 years before to 5 years after IPO and M&A activities.

i. Innovator mobility around IPO

To explore the innovator mobility around IPO, I compare the innovation performance of stayers versus leavers during the three years before the IPO event, and the innovation performance of stayers versus newcomers during the five years after IPO. As shown in **Table 21**, the mean log publication count is used to compare the author-level innovation quantity, and the mean log citation and mean novelty score are used to compare the author-level innovation quality. The orange bars overlaid on the charts for each metric are error bars. For the author types to differ significantly in each innovation metric on average, the error bars must have no overlap.

According to the charts in **Table 21**, stayers produce significantly more publications on average than leavers in pre-IPO years and significantly more publications on average than newcomers in post-IPO years. However, the quality of innovations produced by stayers, leavers, and newcomers is generally not significantly different, though newcomers on average produce publications with significantly higher citations than stayers. As a result, we may infer that the increase in innovation quantity following IPO events might be partially explained by the ability of stayers to publish more articles post-IPO. However, we do not have sufficient evidence to propose that the post-IPO decline in firm-level innovation quality can be explained by the mobility of authors.

ii. Innovator mobility around M&A

I employ the same method on the publication-M&A dataset. As shown in **Table 22**, I compare the innovation performance of stayers versus leavers during the three years before the M&A event, and the innovation performance of stayers versus newcomers during the five years after M&A. I observe that stayers produce significantly more publications on average than leavers in pre-M&A years and significantly more publications on average than newcomers in post-M&A years.

Measured by citation count, the quality of innovations produced by stayers is significantly lower than that of leavers in pre-M&A years and significantly lower than that of newcomers in post-M&A years. Measured by abstract novelty score, however, the quality of innovations produced by stayers is significantly higher than that of leavers in pre-M&A years but does not differ significantly from that of newcomers in post-M&A years.

Therefore, the increase in innovation quantity following M&A events might also come from the higher number of innovations produced by stayers. For innovation quality, my results are contradictory. For example, stayers produce innovations with lower mean citation count but higher novelty score compared with leavers in pre-M&A years. As such, we are unable to obtain consistent findings to show that the observed changes in firm-level innovation quality can result from author mobility.

C. Case Studies on Innovation Novelty of Selected Firms around IPO and M&A Events

According to the previous analyses based on abstract novelty of firms' scientific publications, innovation novelty tends to decrease after firms go public or acquire another company. Nevertheless, the analysis of innovator mobility does not provide sufficient evidence on whether the decline in novelty can be explained by the change in the composition of innovators. While innovation novelty score is found to decrease on the aggregate level following IPO and M&A activities, certain firms may still be able to exhibit growing novelty despite undergoing an IPO and/or M&A. This section turns to individual cases of specific firms so as to examine potential reasons behind the changes in innovation novelty around IPO and M&A activities.

i. Innovation Novelty Score of Cephalon Inc. around IPO

Table 23 shows the changes in innovation novelty score of Cephalon Inc. in years around its IPO (1988-1996). Prior to its acquisition by Teva Pharmaceuticals in 2011, Cephalon was a global pharmaceutical company founded in 1987 and went public in 1991. According to the International Directory of Company Histories (2002), in its pre-IPO years (1987-1991), Cephalon was almost exclusively focused on scientific research, particularly on treatments for multiple sclerosis, strokes, and amyotrophic lateral sclerosis. Although Cephalon did not allocate sufficient resources to developing its sales force and navigating clinical trials, the company was still able to raise funding from investors, secure collaboration contracts with established pharmaceutical firms, and make decent progress on scientific discoveries. Cephalon went public in 1991, but the market's concern of the overvaluation of biotech stocks caused its stock price to drop below the IPO price. As such, the company was under shareholder pressure to generate revenues and earnings. Despite the pressure from the stock market, Cephalon continued its research efforts in the years following the IPO. In 1993, Cephalon acquired rights to develop and sell Provigil, a treatment for narcolepsy, from French company Laboratoire L. Lafon. In 1995, the fourth year after its IPO, Cephalon shifted away from exclusive focus on research to sales force development. In 2000, the company acquired product rights to Actiq, a cancer pain treatment approved by FDA in 1998, through merging with Anesta Corporation. The company later acquired rights to Gabitril, an epilepsy seizure treatment approved in 1997, from Abbot Laboratories.

The changes in novelty score shown in **Table 23** correspond to the crucial activities of Cephalon during the period around its 1991 IPO. Cephalon exhibited increasing innovation novelty in pre-IPO years due to its primary focus on R&D. Nevertheless, following its IPO, the company was faced with significant shareholder pressure to produce solid results, leading to a decline in innovation novelty. The novelty score recovered slightly from 1992 to 1994 because of Cephalon's continued R&D investments in drug development but dropped again in 1995 as the company shifted away from exclusive research focus to building a sales force in order to generate revenues. In addition, the nature of the post-IPO innovation efforts at Cephalon appears to be more incremental than radical, as the rights to some of the most well-sold drugs (e.g., Actiq and Gabitril) were acquired from other companies rather than owned by Cephalon from the initial development stage.

ii. Innovation Novelty Score of Hospira Inc. around M&A

Table 24 shows the change in innovation novelty score of Hospira Inc. in years around its 2006 M&A events (2004-2011). Hospira was created from the spin-off of the hospital products division of Abbot Laboratories in 2004. Before its acquisition by Pfizer in 2015, Hospira was a leading manufacturer of pharmaceutical injectables and medication management systems. According to the International Directory of Company Histories (2014), following its spin-off from Abbot, the company adopted an aggressive plan for increasing R&D investments. New products were developed and launched through both internal manufacturing improvement and acquisitions. In 2006, Hospira acquired Australian company BresaGen which developed peptides and proteins as well as another Australian company Mayne Pharma which enabled Hospira to become the world's largest general injectable pharmaceuticals company. In the years following its 2006 acquisitions, Hospira maintained its focus on research and continued to introduce new products such as irinotecan hydrochloride (an oncology drug) and imipenem-cilastatin (an antibiotic). The company also engaged in strategic collaborations such as a partnership with Bridge Medical to improve the medication management system.

As **Table 24** shows, Hospira experienced a generally increasing novelty trend post-M&A, although the novelty score for firms on the aggregate level tends to decline following M&A activities. The spin-off from Abbot in 2004 enabled Hospira to concentrate resources in R&D spending, and the acquisition of BresaGen and Mayne Pharma in 2006 allowed Hospira to expand internationally. Overall, it appears that Hospira was able to maintain consistent research momentum through a balanced mix of internal development, research collaborations, and acquisitions over its life cycle.

iii. Innovation Novelty Score of Eastman Chemical Company around M&A

Table 25 shows the change in innovation novelty score of Eastman Chemical Company in years around its 1999 M&A event (1996-2004). Created as a result of the spin-off from Eastman Kodak in 1994, Eastman Chemical is a global specialty chemical company that produces chemicals, fibers, and plastics materials. According to the International Directory of Company Histories (2011), Eastman Chemical focused on product innovation and globalization in the initial years after the spin-off in order to maintain a competitive edge in the chemicals market. In 1999, as part of its product innovation strategy, Eastman Chemical acquired Lawter International, a manufacturer of specialty products for ink and coatings. However, due to decreasing demand for chemicals products, Eastman was already faced with production overcapacity by 1997 and had to initiate a restructuring process to reduce operational costs. As a result, the company gradually shifted from product innovation to process innovation. For instance, Eastman set up system-to-system connections with trading partners and established a joint venture with Henderson China Holdings to launch e-commerce websites in China. In 2003, Eastman sold off parts of its coatings, adhesives, specialty polymers, and inks (CASPI) division which was underperforming and reduced workforce. Nevertheless, despite slightly better results through process innovation, the chemicals industry continued to be in a downturn in the early 2000s.

The fluctuations in innovation novelty score in **Table 25** seem to align with Eastman's strategic decisions from 1996 to 2004. Focused on product innovation and globalization in the 1990s, the company had limited room for generating highly novel innovation due to decreasing demand for chemicals products worldwide. As such, the company shifted from product innovation and production capacity improvement to process innovation. The switch to a different innovation area resulted in increasing innovation novelty, but the novelty score still dropped around 2003 due to the continued downturn of the chemicals industry. It appears that the changes in the novelty score of Eastman Chemical Company were more closely related to macroeconomic patterns than to the acquisition of Lawter International in 1999.

iv. Innovation Novelty Score of Millennium Pharmaceuticals around IPO and M&A

Table 26 shows the change in innovation novelty score of Millennium Pharmaceuticals Inc. in years around its 1996 IPO event and 1997 M&A event (1995-2002). Founded in 1993, Millennium Pharmaceuticals is a global pharmaceuticals company specializing in treatments for oncology, inflammation, and metabolic diseases. According to the International Directory of Company Histories (2002), Millennium engaged in R&D primarily through research collaborations. In 1994, the company signed strategic alliance with Hoffmann-La Roche to develop drugs that treat type II diabetes. In 1995, it established a joint venture with Eli Lilly to develop treatment for atherosclerosis and collaborated with Astra AB to target inflammatory diseases. Millennium went public in 1996 as its research efforts started to translate into tangible results. In 1997, Millennium acquired ChemGenics Pharmaceuticals which allowed the company to broaden its development of antibacterial drugs. In the following years, Millennium signed up for more strategic alliances with collaborators including Bayer AG, Bristol-Myers Squibb, and Aventis SA. In 2001, Millennium acquired Cor Therapeutics via a stock swap and gained rights to cardiovascular drugs.

As **Table 26** shows, the innovation novelty score of Millennium Pharmaceuticals was in a declining trend following its 1996 IPO. The company pursued an innovation strategy based primarily on strategic collaborations and acquisitions. As such, the focus on collaborations and acquisitions as opposed to internal drug development may have caused innovation novelty to decline.

Overall, according to the four case studies in this section, it appears that companies which can maintain strong R&D momentum through a balanced combination of internal development and strategic collaborations tend to achieve higher innovation novelty following IPO and M&A events. Nevertheless, as the Eastman Chemical case demonstrates, sometimes the changes in innovation novelty following an IPO or M&A might be more related to fluctuations in industry performance than to the IPO or M&A event specifically.

5. Conclusion

In this paper, I examine the change in firms' innovation performance around IPO and M&A events based on metrics from three modes of innovation – patents, product introductions, and scientific publications. While scholars have primarily focused on only one innovation mode, I consider all three modes to comprehensively measure firms' innovative activities. To assess the quality of innovation, in addition to the citation count metric which has been widely used in the literature, I also consider the abstract novelty score in the case of scientific publications in order to conduct a more in-depth examination of the innovative content of each innovation. After examining a variety of innovation modes and metrics, I find that innovation quantity increases while innovation quality decreases following IPO and M&A events. The results are generally consistent among patent-based, product-based, and publication-based metrics, and confirm with the results from previous literature.

In addition to exploring how innovation performance varies with IPO and M&A status, I also control for industry characteristics (sales concentration, turbulence, and geographic concentration) and firm-level financial metrics (total assets, net income to total assets, cash to total assets, and R&D to total assets). In general, higher sales concentration and geographic concentration relate to lower innovation quantity (number of innovations) in post-event years than in pre-event years, possibly due to reduced incentives to produce high quantity of innovations when the market in post-event years is more concentrated, barriers to entry are higher, and resources and collaborators are more reachable. However, higher sales concentration and geographic concentration tend to correlate with higher innovation quality (novelty of innovation) in post-event years than in pre-event years, possibly because firms have higher capacity to focus on generating economic value from truly novel innovations when the market in post-event years is more financially and geographically concentrated. As Feldman (1993) shows, "innovation is found to cluster geographically in areas which contain concentrations of specialized resources which enhance and facilitate the innovation process." In terms of financial metrics, firms that exhibit larger asset and cash holdings, higher profitability, and more R&D investments are generally more innovative in terms of both quality and quantity.

Overall, despite the ability to produce more innovations after going public or acquiring another company, firms need to be mindful of the potential loss in innovation quality. Innovation is a long-term task crucial to a firm's long-term performance, but firms might be subject to higher shareholder pressure once they go public or experience a change in the composition of major shareholders following an M&A. As such, firms may be pressured to satisfy short-term earnings at the expense of long-term performance. Although the study of innovator mobility in this paper does not provide sufficient insights on whether the changes in innovation performance around strategic events are explained by the changes in the composition of innovators, it is still reasonable to believe that the restructuring of the talent base following strategic events can exert substantial influence on a firm's innovation capacity, whether positively or negatively. Moreover, the case studies on specific firms show that firms which can maintain innovation momentum through a balanced combination of internal development and strategic collaborations following IPO and M&A events tend to exhibit increasing novelty score, while companies that focus too much on generating revenues or pursue an unbalanced innovation strategy tend to experience declines in novelty. Therefore, it would be essential for firms to develop strategies to maintain and enhance innovation quality and avoid disruptions to innovative capacity.

6. Discussion

A. Significance

This paper could be helpful to corporate strategy researchers and experts, especially those who focus on corporate innovation. Instead of restricting the measurement of innovation to patent-based metrics, the paper discusses alternative sources of innovation such as new scientific publications and new product introductions and aims to improve the measurement of innovation quality through textual analysis of article abstracts. By proposing a more comprehensive measure of innovation performance, this paper could help future researchers to gain a more systematic understanding of innovation and open up new perspectives as they explore the innovative practices of firms and how they relate to various aspects of firm performance.

The paper could also be relevant to firms as they attempt to continuously improve their innovation performance in order to achieve competitive advantages against their peers. For example, the proposed innovation novelty score should help firms to more accurately assess their innovation quality relative to their competitors. The findings on innovator mobility and the case studies on specific firms around IPO and M&A activities may also be useful as firms make their strategic decisions on whether to go public or engage in a merger or acquisition.

B. Limitations and Ideas for Future Work

This research contains some limitations as well. First, when analyzing the change in innovation around M&A events, I only include M&A transactions involving public acquirers, as most target firms would disappear following an acquisition. However, some target firms may remain as separate subsidiaries of their corresponding acquirer firms after acquisitions, so some patents may be assigned to the target firm rather than to the acquirer firm, despite the fact that the innovation comes from the acquirer firm as a whole. As such, this analysis may underestimate the innovation output following M&A events. Nevertheless, simply adding the patents of post-acquisition target firms to the set of patents from the parent firms would not work as the Thomson SDC database only contains M&A transactions involving public firms. Some public parent firms may have acquired private subsidiary firms that operate as a standalone entity in the US patent system and do not show up in the patent database. In order to mitigate the underestimation problem, it would be better to utilize a database that contains M&A transactions involving both public and private firms so that private acquirers and targets are not excluded from the analysis.

Second, the regression analyses on within-firm variations in innovation performance are endogenous in itself and prone to self-selection bias. According to Bernstein (2015), firms may choose to go public at a specific stage in their respective life cycle. For example, firms might be more likely to go public when they have achieved highly novel innovations, so the regression to measure how innovation relates to IPO status might be subject to the effect of life cycle as a confounding variable. In addition, my results are primarily based on OLS linear regression analysis, so I have only established relationships between innovation performance and IPO or M&A status. In order to examine whether the post-event increase in innovation quantity and decrease in innovation quality are indeed caused by the strategic event itself, I would need to compare the innovation of firms that underwent the event with that of similar firms that did not. Hence, in future work, I could follow Bernstein (2015) to compare the post-IPO innovation performance of firms that actually went public with that of similar firms that filed for IPO but did not go public eventually. The same method would apply to the M&A case.

Third, my calculation of the novelty score for scientific publications might also contain algorithmic errors. Because Scopus does not contain unique identifiers for firm names, I manually input firm names into Scopus' web search query to download basic publication information and then match the firm names in the downloaded data to GVKEY identifiers. Because there might be multiple variations of a firm's name, the matching process may be crude and incomplete. In addition, in order to focus on only innovative words in the abstract text-mining analysis, I remove the stop words identified by the SMART information retrieval system. Nevertheless, the removal process might not be exhaustive and there might be certain commonly-used words or phrases that should not be considered as innovative content. In future work, instead of applying a built-in stop-word list such as SMART, I would need to conduct an analysis on Term Frequency–Inverse Document Frequency (TF-IDF) to investigate how important each abstract word is to the scientific publications in my collection. In this way, I could effectively remove words that are not novel enough in scientific research.

Fourth, I have been able to analyze the three innovation modes (patents, product introductions, and scientific publications) separately in this paper, but the observed relationships could be verified in the future through exploring all three innovation modes collectively to analyze the association and causation between overall firm innovation and strategic activities. According to Murray and Stern (2007), scientific publications tend to pre-date patent grants and publication citations tend to decline following patent grants. Therefore, one potential way to consolidate patents and publications is to place a higher weight on publication-based metrics prior to patent grant and a higher weight on patent-based metrics after the patent grant. This approach should help researchers to obtain a more comprehensive understanding of firm innovation.

Last but not the least, as employee mobility increases and information exchange becomes more convenient, companies have been transitioning from an internal and closed innovation strategy to a combination of internal development and open innovation. Scholars have demonstrated that an open innovation process facilitates innovators to adopt a solution-seeking mindset and focus on the big picture of why an innovation is needed (Lifshitz-Assaf, Tushman, and Lakhani 2018). Open innovation is also found to broaden a firm's knowledge and expertise by enabling the firm to venture into new technological areas and strengthen existing areas that are still insufficient (Shin et al. 2017). However, while firms may intend to source distant knowledge through open innovation, the process of sourcing external ideas might actually narrow their perspective as they are more likely to focus on knowledge areas that are more familiar to them (Piezunka and Dahlander 2015).

In this research paper, I investigate how firm innovation as a whole changes around IPO and M&A activities but do not distinguish between closed and open innovation. In order to contribute to the field of research on open innovation, I could expand the scope of this paper by analyzing how the performance of open innovation changes around firms' IPO and M&A activities. One approach would be to analyze the change in collaboration pattern around IPO and M&A events. Following Belderbos et al. (2014), I can classify the collaborators of each patent or scientific publication into intra-industry partners or competitors, inter-industry partners or complementors, and universities. Then, I would explore the change in the composition of collaborators around IPO and M&A and how the collaboration pattern relates to the quantity and quality of open innovation. In addition, I could also calculate an "innovation openness ratio" for each firm based on the framework proposed by Michelino et al. (2015) and examine how the openness ratio fluctuates around IPO and M&A events. A third way of measuring open innovation could be based on a firm's usage of open source software in its innovative activities (Nagle 2018). The study of how open innovation relates to IPO and M&A events should provide insights into whether enhanced access to financial and strategic resources following an IPO or M&A event would enable a firm to enhance the scale and quality of its open innovation efforts.

7. References

Aggarwal, Vikas A., and David H. Hsu. "Entrepreneurial exits and innovation." *Management Science* 60, no. 4 (2013): 867-887. https://pubsonline.informs.org/doi/abs/10.1287/mnsc.2013.1801.

Asker, John, Joan Farre-Mensa, and Alexander Ljungqvist. "Corporate investment and stock market listing: A puzzle?" *The Review of Financial Studies* 28, no. 2 (2014): 342-390. http://ecgi.global/sites/default/files/working_papers/documents/SSRN-id1603484.pdf.

Bena, Jan, and Kai Li. "Corporate innovations and mergers and acquisitions." *The Journal of Finance* 69, no. 5 (2014): 1923-1960. https://www.jstor.org/stable/pdf/43612948.pdf.

Belderbos, Rene, Bruno Cassiman, Dries Faems, Bart Leten, and Bart Van Looy. "Co-ownership of intellectual property: Exploring the value-appropriation and value-creation implications of co-patenting with different partners." *Research Policy* 43, no. 5 (2014): 841-852. https://www.sciencedirect.com/science/article/pii/S0048733313001583.

Bernstein, Shai. "Does going public affect innovation?." *The Journal of Finance* 70, no. 4 (2015): 1365-1403. https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12275.

Calantone, Roger J., S. Tamer Cavusgil, and Yushan Zhao. "Learning orientation, firm innovation capability, and firm performance." *Industrial Marketing Management* 31, no. 6 (2002): 515-524. https://www.sciencedirect.com/science/article/abs/pii/S0019850101002036.

"Cephalon, Inc." In *International Directory of Company Histories*, edited by Jay P. Pederson, 93-96. Vol. 45. Detroit, MI: St. James Press, 2002. *Gale Virtual Reference Library*. http://proxy.library.upenn.edu:2084/apps/doc/CX2844900031/GVRL?u=upenn_main&sid=GVRL&xid=1beb8d47.

Cloodt, Myriam, John Hagedoorn, and Hans Van Kranenburg. "Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries." *Research Policy* 35, no. 5 (2006): 642-654. https://www.sciencedirect.com/science/article/pii/S004873330600045X.

Covell, Jeffrey L., and Mary Tradii. "Hospira, Inc." In *International Directory of Company Histories*, edited by Jay P. Pederson, 287-292. Vol. 148. Detroit, MI: St. James Press, 2014. *Gale Virtual Reference Library*. http://proxy.library.upenn.edu:2084/apps/doc/CX2784900065/GVRL?u=upenn_main&sid=GVRL&xid=8e2651a1.

Covell, Jeffrey L., Updated Stephen Meyer, and Aaron Hauser. "Eastman Chemical Company." In *International Directory of Company Histories*, edited by Drew Johnson, 207-212. Vol. 116. Detroit, MI: St. James Press, 2011. *Gale Virtual Reference Library*. http://proxy.library.upenn.edu:2084/apps/doc/CX2355900054/GVRL?u=upenn_main&sid=GVRL&xid=4e845ab7.

Dumais, Guy, Glenn Ellison, and Edward L. Glaeser. "Geographic concentration as a dynamic process." *Review of economics and Statistics* 84, no. 2 (2002): 193-204. http://web.mit.edu/gellison/www/deg107.pdf.

Feldman, Maryann P. "An examination of the geography of innovation." *Industrial and Corporate Change* 2, no. 3 (1993): 451-470. https://academic.oup.com/icc/article-abstract/2/3/451/768563.

Gao, Huasheng, Po-Hsuan Hsu, and Kai Li. "Innovation strategy of private firms." Journal of Financial and Quantitative Analysis 53, no. 1 (2018): 1-32. https://www.ssrn.com/abstract=2407075.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. “The NBER patent citation data file: Lessons, insights and methodological tools.” *National Bureau of Economic Research*, no. w8498 (2001). https://www.nber.org/papers/w8498.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. "Market value and patent citations." *RAND Journal of economics* (2005): 16-38. https://www.jstor.org/stable/pdf/1593752.pdf.

He, Jie Jack, and Xuan Tian. "The dark side of analyst coverage: The case of innovation." *Journal of Financial Economics* 109, no. 3 (2013): 856-878. https://www.sciencedirect.com/science/article/pii/S0304405X13001086.

“Innovation Measurement.” *Department of Commerce* (2007). https://www.gpo.gov/fdsys/pkg/FR-2007-04-13/pdf/07-1827.pdf.

Jain, Bharat A., and Omesh Kini. "The post‐issue operating performance of IPO firms." The *Journal of Finance* 49, no. 5 (1994): 1699-1726. https://www.jstor.org/stable/pdf/2329268.pdf.

Lifshitz-Assaf, Hila, Michael Tushman, and Karim R. Lakhani. “A study of NASA scientists shows how to overcome barriers to open innovation.” *Harvard Business Review* (2018). https://hbr.org/2018/05/a-study-of-nasa-scientists-shows-how-to-overcome-barriers-to-open-innovation.

Matraves, Catherine, and Laura Rondi. "Product differentiation, industry concentration and market share turbulence." *International Journal of the Economics of Business* 14, no. 1 (2007): 37-57. http://www.ceris.cnr.it/ceris/workingpaper/2005/WP_14_05_RONDI_.pdf.

Michelino, Francesca, Emilia Lamberti, Antonello Cammarano, and Mauro Caputo. "Measuring open innovation in the Bio-Pharmaceutical industry." *Creativity and Innovation Management* 24, no. 1 (2015): 4-28. https://onlinelibrary.wiley.com/doi/abs/10.1111/caim.12072.

"Millennium Pharmaceuticals, Inc." In *International Directory of Company Histories*, edited by Jay P. Pederson, 249-252. Vol. 47. Detroit, MI: St. James Press, 2002. *Gale Virtual Reference Library*. http://proxy.library.upenn.edu:2084/apps/doc/CX2845100069/GVRL?u=upenn_main&sid=GVRL&xid=abc44d46.

Murray, Fiona, and Scott Stern. "Do formal intellectual property rights hinder the free flow of scientific knowledge?: An empirical test of the anti-commons hypothesis." *Journal of Economic Behavior & Organization* 63, no. 4 (2007): 648-687. http://users.nber.org/~marschke/mice/Papers/murraystern.pdf.

Nagle, Frank. "Open source software and firm productivity." *Management Science* (2018). https://www.ssrn.com/abstract=2559957.

Piezunka, Henning, and Linus Dahlander. "Distant search, narrow attention: How crowding alters organizations' filtering of suggestions in crowdsourcing." *Academy of Management Journal* 58, no. 3 (2015): 856-880. https://journals.aom.org/doi/abs/10.5465/amj.2012.0458.

Ramaswamy, K. P., and James F. Waegelein. "Firm financial performance following mergers." Review of Quantitative Finance and Accounting 20, no. 2 (2003): 115-126. https://link.springer.com/article/10.1023/A:1023089924640.

Shin, Seungryul Ryan, John Han, Klaus Marhold, and Jina Kang. "Reconfiguring the firm's core technological portfolio through open innovation: focusing on technological M&A." *Journal of Knowledge Management* 21, no. 3 (2017): 571-591. https://www.emeraldinsight.com/doi/abs/10.1108/JKM-07-2016-0295.

Wies, Simone, and Christine Moorman. "Going public: how stock market listing changes firm innovation behavior." *Journal of Marketing Research* 52, no. 5 (2015): 694-709. https://search.proquest.com/docview/1735914072.

Wu, Lynn, Bowen Lou, and Lorin M. Hitt. "Data Analytics Supports Decentralized Innovation." *Management Science*, Forthcoming (2019). https://www.ssrn.com/abstract=3351982.

Zuo, Zhiya, Kang Zhao, and David Eichmann. "The state and evolution of US iSchools: From talent acquisitions to research outcome." *Journal of the Association for Information Science and Technology* 68, no. 5 (2017): 1266-1277. https://doi.org/10.1002/asi.23751.

Appendix

Table 1. Summary Statistics of Patent-IPO Dataset

This table displays summary statistics of the patent applications of firms from three years before to five years after going public. Section A displays the distribution of patent applications across 6 major tech classes. Sections B and C show the average innovation measures during 3 years before IPO and during 5 years after IPO, respectively. Section D lists the IPO filing, patent applications, and patent grants by year.

Section A – Distribution of patents across 6 major tech classes

	Number of Patents	Percentage
Chemicals	12499	13.8%
Computer and Communications	28018	31.0%
Drugs and Medicine	14092	15.6%
Electronics	20653	22.9%
Mechanical	9122	10.1%
Others	5954	6.6%
	90338	100.0%

Section B – Average innovation measures during 3 years before IPO

	Mean	Median	Standard Deviation
Patent Count	6.79	2.00	30.25
Citations	12.79	5.00	24.88
Generality	0.55	0.63	0.32
Originality	0.54	0.61	0.32

Section C – Average innovation measures during 5 years after IPO

	Mean	Median	Standard Deviation
Patent Count	10.48	2.00	52.38
Citations	6.51	2.00	13.77
Generality	0.54	0.63	0.34
Originality	0.55	0.63	0.32

Section D – IPO Filing, Patent Applications, and Patent Grants by Year

Year	IPO Filing	Patent Applications	Patent Grants
1975	0	0	0
1976	0	3	0
1977	0	1	2
1978	2	7	2
1979	2	4	2
1980	1	6	5
1981	1	18	2
1982	0	28	6
1983	3	43	20
1984	4	439	24
1985	4	934	158
1986	52	1024	476
1987	139	1165	919
1988	56	1468	1043
1989	39	1736	1364
1990	41	2018	1503
1991	120	2292	1742
1992	137	2775	2010
1993	200	2687	2300
1994	163	3480	2510
1995	193	5684	2333
1996	306	6035	2887
1997	204	8040	3939
1998	151	8600	5867
1999	231	9395	6886
2000	222	9206	7497
2001	15	9217	8281
2002	9	7403	8242
2003	8	4497	8321
2004	46	1856	7994
2005	34	269	6697
2006	19	8	7306
2007	7	0	0
	2409	90338	90338

Table 2. Within-Firm Change in Patent Count around IPO

This table shows the changes in patent count around IPO. I use the natural logarithm of the patent count to reduce skewness in the data. To avoid any zero values, I add one to the patent count when taking the natural logarithm. The regression in Column (1) only considers IPO status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-IPO status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets.

	Log Patent Count		
	(1)	(2)	(3)
IPO-3	−0.194*** (0.029)	−0.268*** (0.035)	0.062 (0.091)
IPO-2	−0.127*** (0.026)	−0.199*** (0.032)	0.079* (0.044)
IPO-1	−0.022 (0.024)	−0.092*** (0.031)	0.134*** (0.038)
IPO+1	0.062*** (0.023)	0.062*** (0.023)	0.054** (0.024)
IPO+2	0.034 (0.024)	0.034 (0.024)	0.015 (0.025)
IPO+3	0.051** (0.025)	0.051** (0.025)	0.039 (0.027)
IPO+4	0.065** (0.027)	0.066** (0.027)	0.057** (0.029)
IPO+5	0.084*** (0.029)	0.085*** (0.029)	0.054* (0.032)
Industry Concentration (HHI)		0.324** (0.147)	0.329 (0.241)
Turbulence		0.118 (0.121)	−0.129 (0.168)
Geographic Dispersion (EGI)		0.003 (0.013)	0.041 (0.049)
Log Total Assets			0.213*** (0.008)
Net Income / Total Assets			−0.007 (0.008)
Cash / Total Assets			0.081** (0.038)
RD / Total Assets			0.140*** (0.026)
Post-IPO * HHI		−0.482*** (0.146)	−0.286 (0.217)
Post-IPO * Turbulence		−0.153 (0.149)	0.122 (0.191)
Post-IPO * EGI		−0.017 (0.024)	−0.076* (0.046)
Constant	1.063*** (0.072)	1.074*** (0.077)	0.146 (0.096)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	9,868	9,860	7,300
Log Likelihood	−10,056.060	−10,054.580	−7,201.511
Akaike Inf. Crit.	20,136.120	20,145.160	14,447.020
Bayesian Inf. Crit.	20,222.480	20,274.690	14,598.730

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include IPO Status
(2) Includes IPO Status, HHI, Turbulence, EGI, and interactions
(3) Includes IPO Status, HHI, Turbulence, EGI, interactions, and financials

Table 3. Within-Firm Change in Patent Quality Metrics around IPO

This table shows the changes in three patent quality metrics around IPO. I use the natural logarithm of the citation count to reduce skewness in the data. To avoid any zero values, I add one to the citation count when taking the natural logarithm. Column (1) shows the change in average log citation count, Column (2) shows the change in average generality (degree to which a patent is cited by patents from a more diverse range of technology classes), and Column (3) shows the change in average originality (degree to which a patent is citing a broader set of technology classes). Independent variables include IPO status dummies, industry metrics (sales concentration HHI, turbulence, and geographic concentration EGI), and their interactions with post-IPO status.

	Dependent variable:		
	Log Average Citation Count	Average Generality	Average Originality
	(1)	(2)	(3)
IPO-3	0.125*** (0.040)	0.030* (0.017)	0.013 (0.014)
IPO-2	0.129*** (0.037)	0.007 (0.016)	−0.002 (0.013)
IPO-1	0.093*** (0.035)	0.015 (0.015)	0.008 (0.013)
IPO+1	−0.070*** (0.027)	0.007 (0.012)	0.006 (0.009)
IPO+2	−0.120*** (0.028)	0.023* (0.012)	0.0004 (0.010)
IPO+3	−0.176*** (0.029)	0.022* (0.013)	0.008 (0.010)
IPO+4	−0.181*** (0.030)	0.020 (0.014)	0.001 (0.010)
IPO+5	−0.197*** (0.033)	−0.016 (0.015)	0.003 (0.010)
Industry Concentration (HHI)	0.229 (0.161)	0.041 (0.058)	−0.003 (0.053)
Turbulence	−0.343** (0.140)	0.105* (0.061)	−0.021 (0.052)
Geographic Concentration (EGI)	0.007 (0.015)	−0.001 (0.005)	0.005 (0.005)
Post-IPO * HHI	0.286* (0.167)	0.048 (0.071)	0.029 (0.059)
Post-IPO * Turbulence	0.241 (0.172)	−0.047 (0.078)	0.077 (0.064)
Post-IPO * EGI	0.036 (0.027)	0.009 (0.011)	−0.003 (0.009)
Constant	1.949*** (0.175)	0.521*** (0.013)	0.528*** (0.011)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	9,860	5,196	7,800
Log Likelihood	−11,217.760	−173.836	142.972
Akaike Inf. Crit.	22,471.530	383.671	−249.944
Bayesian Inf. Crit.	22,601.060	501.673	−124.630

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4. Summary Statistics of Patent-M&A Dataset

This table displays summary statistics of the patent applications of firms from three years before to five years after M&A transactions. Section A displays the distribution of patent applications across 6 major tech classes. Sections B and C show the average innovation measures during 3 years before M&A and during 5 years after M&A, respectively. Section D lists the M&A deals, patent applications, and patent grants by year.

Section A – Distribution of patents across 6 major tech classes

	Number of Patents	Percentage
Chemicals	61575	13.0%
Computer and Communications	165714	35.0%
Drugs and Medicine	27917	5.9%
Electronics	125110	26.4%
Mechanical	54017	11.4%
Others	38690	8.2%
	473023	100.0%

Section B – Average innovation measures during 3 years before M&A

	Mean	Median	Standard Deviation
Patent Count	76.62	6.00	275.21
Citations	7.83	3.00	13.86
Generality	0.50	0.57	0.34
Originality	0.50	0.57	0.33

Section C – Average innovation measures during 5 years after M&A

	Mean	Median	Standard Deviation
Patent Count	78.17	7.00	267.20
Citations	5.03	1.00	10.59
Generality	0.48	0.54	0.36
Originality	0.50	0.57	0.33

Section D – M&A Deals, Patent Applications, and Patent Grants by Year

Year	M&A Deals	Patent Applications	Patent Grants
1975	0	0	0
1976	0	0	0
1977	0	789	10
1978	0	1469	347
1979	0	1823	713
1980	4	2395	1341
1981	26	3173	1844
1982	40	3662	2216
1983	36	4384	2813
1984	38	5233	3965
1985	32	6247	4816
1986	47	6917	5392
1987	60	7673	7071
1988	69	8999	7049
1989	73	10003	9083
1990	40	10517	8897
1991	63	10899	9920
1992	96	13429	10212
1993	108	13547	11309
1994	141	17197	12510
1995	98	22405	12998
1996	97	27536	15750
1997	180	34855	17507
1998	205	36251	25802
1999	251	41577	28772
2000	256	48483	31565
2001	151	47829	35717
2002	107	40388	38495
2003	121	27549	41904
2004	103	13725	42104
2005	127	3882	37304
2006	113	187	45597
2007	97	0	0
2008	51	0	0
2009	11	0	0
	2841	473023	473023

Table 5. Within-Firm (Acquirer) Change in Patent Count around M&A

This table shows the changes in patent count around M&A for acquirers. I use the natural logarithm of the patent count to reduce skewness in the data. To avoid any zero values, I add one to the patent count when taking the natural logarithm. The regression in Column (1) only considers M&A status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-M&A status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets.

	Log Patent Count		
	(1)	(2)	(3)
MA-3	−0.116*** (0.021)	−0.153*** (0.028)	−0.058* (0.030)
MA-2	−0.061*** (0.021)	−0.097*** (0.028)	−0.025 (0.030)
MA-1	−0.033 (0.021)	−0.071** (0.028)	−0.024 (0.029)
MA+1	0.017 (0.022)	0.017 (0.022)	0.002 (0.023)
MA+2	0.007 (0.022)	0.007 (0.022)	0.005 (0.023)
MA+3	0.027 (0.023)	0.027 (0.023)	0.068*** (0.024)
MA+4	0.001 (0.024)	0.002 (0.024)	0.056** (0.026)
MA+5	0.003 (0.025)	0.003 (0.025)	0.070*** (0.027)
Industry Concentration (HHI)		−0.196 (0.166)	−0.229 (0.192)
Turbulence		−0.025 (0.132)	−0.077 (0.142)
Geographic Dispersion (EGI)		−0.006 (0.023)	0.008 (0.029)
Log Total Assets			0.426*** (0.010)
Net Income / Total Assets			0.020 (0.026)
Cash / Total Assets			0.126** (0.057)
RD / Total Assets			1.106*** (0.083)
Post-MA * HHI		−0.221* (0.131)	−0.356** (0.153)
Post-MA * Turbulence		−0.153 (0.163)	−0.355** (0.180)
Post-MA * EGI		0.003 (0.023)	−0.013 (0.029)
Constant	1.491*** (0.149)	1.558*** (0.151)	−0.746*** (0.196)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	14,302	14,287	11,649
Log Likelihood	−15,808.200	−15,793.470	−12,065.490
Akaike Inf. Crit.	31,640.410	31,622.930	24,174.970
Bayesian Inf. Crit.	31,731.230	31,759.140	24,336.960

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include MA Status
(2) Includes MA Status, as well as HHI, Turbulence, EGI, and interactions
(3) Includes MA Status, HHI, Turbulence, EGI, interactions, and financials

Table 6. Within-Firm (Acquirer) Change in Patent Quality Metrics around M&A

This table shows the changes in three patent quality metrics around M&A for acquirers. I use the natural logarithm of the citation count to reduce skewness in the data. To avoid any zero values, I add one to the citation count when taking the natural logarithm. Column (1) shows the change in log average citation count, Column (2) shows the change in average generality (degree to which a patent is cited by a more technologically varied array of patents), and Column (3) shows the change in average originality (degree to which a patent is citing a broader array of technology classes). Independent variables include M&A status dummies, industry metrics (sales concentration HHI, turbulence, and geographic concentration EGI), and their interactions with post-M&A status.

	Dependent variable:		
	Log Average Citation Count	Average Generality	Average Originality
	(1)	(2)	(3)
IPO-3	0.085*** (0.021)	0.018 (0.017)	0.0002 (0.012)
IPO-2	0.066*** (0.020)	0.001 (0.017)	0.003 (0.011)
IPO-1	0.053*** (0.020)	−0.005 (0.017)	0.002 (0.011)
IPO+1	−0.006 (0.016)	0.007 (0.013)	0.005 (0.009)
IPO+2	−0.005 (0.017)	0.015 (0.014)	0.016* (0.009)
IPO+3	−0.002 (0.017)	−0.013 (0.015)	−0.003 (0.010)
IPO+4	0.002 (0.018)	0.008 (0.016)	0.016* (0.010)
IPO+5	−0.012 (0.019)	−0.003 (0.017)	0.009 (0.010)
Industry Concentration (HHI)	−0.043 (0.112)	0.279*** (0.079)	0.193*** (0.057)
Turbulence	0.058 (0.097)	0.112* (0.063)	−0.053 (0.056)
Geographic Concentration (EGI)	−0.011 (0.017)	0.035** (0.015)	0.013 (0.009)
Post-IPO * HHI	0.308*** (0.095)	−0.074 (0.078)	−0.063 (0.053)
Post-IPO * Turbulence	0.049 (0.120)	−0.185** (0.080)	0.089 (0.067)
Post-IPO * EGI	0.014 (0.017)	−0.035** (0.016)	−0.013 (0.009)
Constant	1.819*** (0.180)	0.514*** (0.015)	0.520*** (0.011)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	14,287	4,104	7,676
Log Likelihood	−10,752.660	192.843	1,067.501
Akaike Inf. Crit.	21,541.330	−349.686	−2,099.002
Bayesian Inf. Crit.	21,677.540	−235.931	−1,973.977
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 7. Summary Statistics of Product-M&A Dataset

This table displays summary statistics of the product introductions of firms from three years before to five years after M&A transactions. Section A displays the distribution of product introductions across 7 major product sectors. Sections B and C show the average innovation measures during 3 years before M&A and during 5 years after M&A, respectively. Section D lists the M&A deals and total product introductions by year.

Section A – Distribution of product introductions across 7 major product sectors

	Number of Products	Percentage
Business	3208	4.4%
Consumer	11973	16.5%
Energy	910	1.3%
Healthcare	22596	31.1%
Industrial	5585	7.7%
Technology	27345	37.6%
Others	1070	1.5%
	72687	100.0%

Section B – Average innovation measures during 3 years before M&A

	Mean	Median	Standard Deviation
Total Product Count	67.29	16.00	188.86
Breakthrough Product Count	1.06	0.00	2.76

Section C – Average innovation measures during 5 years after M&A

	Mean	Median	Standard Deviation
Total Product Count	69.86	18.00	187.09
Breakthrough Product Count	0.84	0.00	2.71

Section D – M&A Deals and Total Product Introductions by Year

Year	M&A Deals	Total Product Introductions
1998	147	0
1999	142	0
2000	155	0
2001	98	0
2002	78	0
2003	102	18518
2004	94	4101
2005	131	2915
2006	205	4231
2007	185	5532
2008	149	3717
2009	102	3411
2010	120	5630
2011	146	5101
2012	175	4269
2013	124	4098
2014	149	3381
2015	132	1968
2016	128	1971
2017	88	1931
2018	2	1913
	2652	72687

Table 8. Within-Firm Change in Total Product Introductions around M&A

This table shows the changes in total product count around M&A for acquirers. I use the natural logarithm of the total product count to reduce skewness in the data. To avoid any zero values, I add one to the product count when taking the natural logarithm. The regression in Column (1) only considers M&A status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-M&A status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets.

	Log Total Product Introductions		
	(1)	(2)	(3)
MA-3	−0.163*** (0.038)	−0.159*** (0.047)	−0.149*** (0.057)
MA-2	−0.076** (0.037)	−0.074 (0.046)	−0.039 (0.056)
MA-1	−0.102*** (0.036)	−0.100** (0.046)	−0.066 (0.055)
MA+1	0.040 (0.034)	0.039 (0.034)	−0.008 (0.042)
MA+2	0.044 (0.034)	0.043 (0.035)	0.040 (0.042)
MA+3	−0.033 (0.035)	−0.035 (0.035)	−0.059 (0.043)
MA+4	−0.009 (0.035)	−0.013 (0.035)	−0.033 (0.043)
MA+5	−0.066* (0.035)	−0.057 (0.035)	−0.095** (0.043)
Industry Concentration (HHI)		−0.744*** (0.262)	−1.271*** (0.365)
Turbulence		0.204 (0.289)	0.082 (0.421)
Geographic Concentration (EGI)		0.002 (0.044)	−0.047 (0.061)
Log Total Assets			0.231*** (0.014)
Net Income / Total Assets			−0.026 (0.032)
Cash / Total Assets			−0.020 (0.105)
RD / Total Assets			0.214** (0.107)
Post-MA * HHI		−0.026 (0.222)	0.148 (0.289)
Post-MA * Turbulence		−0.186 (0.321)	−0.326 (0.506)
Post-MA * EGI		−0.035 (0.043)	0.004 (0.050)
Constant	2.495*** (0.110)	2.597*** (0.115)	1.182*** (0.173)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	13,594	13,308	9,166
Log Likelihood	−20,003.270	−19,500.390	−13,473.610
Akaike Inf. Crit.	40,030.540	39,036.780	26,991.230
Bayesian Inf. Crit.	40,120.750	39,171.710	27,147.940
Note:	*p<0.1; **p<0.05; ***p<0.01		

(1) Independent variables only include MA Status
(2) Includes MA Status, as well as HHI, Turbulence, EGI, and interactions
(3) Includes MA Status, HHI, Turbulence, EGI, interactions, and financials

Table 9. Within-Firm Change in Breakthrough Product Introductions around M&A

This table shows the changes in breakthrough product count around M&A for acquirers. I use the natural logarithm of the breakthrough product count to reduce skewness in the data. To avoid any zero values, I add one to the product count when taking the natural logarithm. The regression in Column (1) only considers M&A status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-M&A status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets.

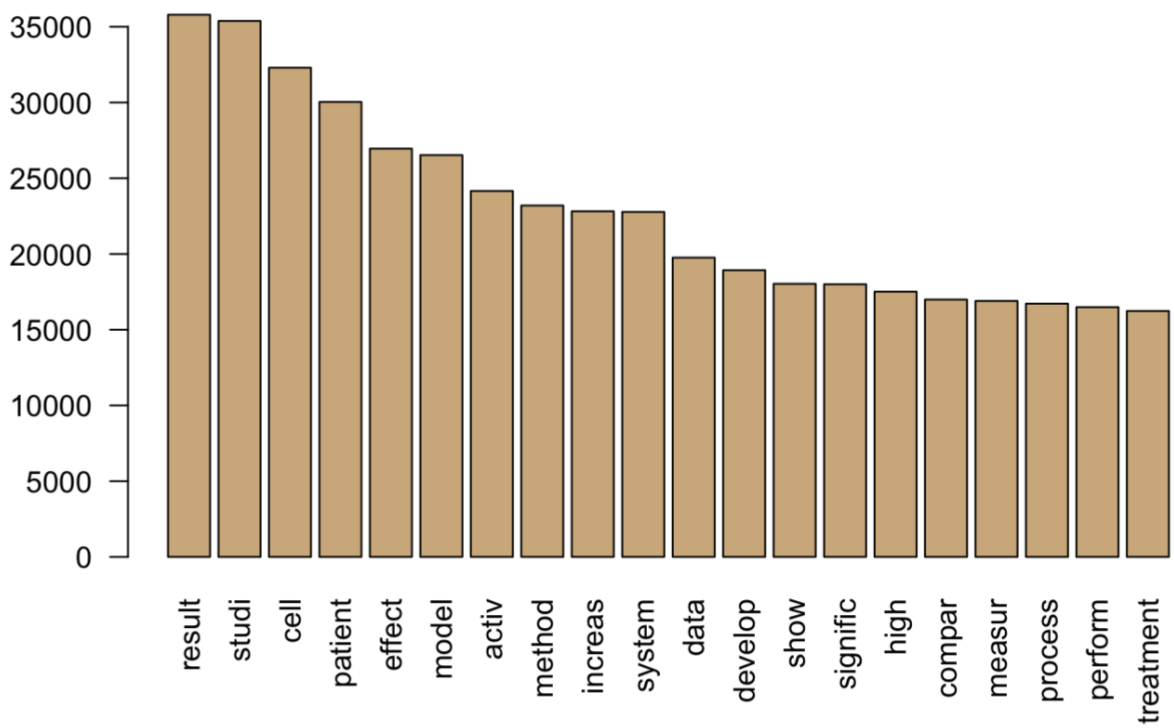
	Log Breakthrough Product Introductions		
	(1)	(2)	(3)
MA-3	−0.044*** (0.017)	−0.069*** (0.021)	−0.068** (0.027)
MA-2	−0.029* (0.016)	−0.054** (0.021)	−0.054** (0.026)
MA-1	−0.060*** (0.016)	−0.086*** (0.020)	−0.078*** (0.026)
MA+1	−0.066*** (0.015)	−0.067*** (0.015)	−0.077*** (0.019)
MA+2	−0.097*** (0.015)	−0.098*** (0.016)	−0.104*** (0.020)
MA+3	−0.110*** (0.016)	−0.110*** (0.016)	−0.128*** (0.020)
MA+4	−0.095*** (0.016)	−0.094*** (0.016)	−0.109*** (0.020)
MA+5	−0.126*** (0.016)	−0.124*** (0.016)	−0.133*** (0.020)
Log Total Product Count	0.136*** (0.003)	0.138*** (0.004)	0.137*** (0.005)
Industry Concentration (HHI)		0.272*** (0.098)	0.207 (0.138)
Turbulence		0.140 (0.129)	−0.152 (0.195)
Geographic Concentration (EGI)		0.032* (0.018)	0.015 (0.023)
Log Total Assets			−0.001 (0.004)
Net Income / Total Assets			0.005 (0.013)
Cash / Total Assets			−0.096** (0.041)
RD / Total Assets			0.038 (0.046)
Post-MA * HHI		−0.182* (0.097)	−0.039 (0.133)
Post-MA * Turbulence		−0.080 (0.144)	0.272 (0.234)
Post-MA * EGI		−0.032* (0.018)	−0.024 (0.022)
Constant	0.024 (0.085)	0.002 (0.086)	0.025 (0.101)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	13,594	13,308	9,166
Log Likelihood	−8,467.084	−8,351.509	−6,198.254
Akaike Inf. Crit.	16,960.170	16,741.020	12,442.510
Bayesian Inf. Crit.	17,057.900	16,883.440	12,606.340

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include MA Status
(2) Includes MA Status, as well as HHI, Turbulence, EGI, and interactions
(3) Includes MA Status, HHI, Turbulence, EGI, interactions, and financials

Table 10. Summary Charts from Abstract Text-Mining

This table displays summary charts from text mining of the words in the abstracts of the scientific articles published by firms. Section A displays the 20 most commonly-used words in abstracts and their respective frequencies. Some words appear to be incomplete because I have stemmed each word (removed any inflectional affixes in each word) in order to ensure that all forms of each word have been captured. Section B shows a word cloud generated from the set of stemmed words, with visually larger words being more common.

Section A – The 20 Most Common Words in the Abstracts of Scientific Publications



Section B – Word Cloud

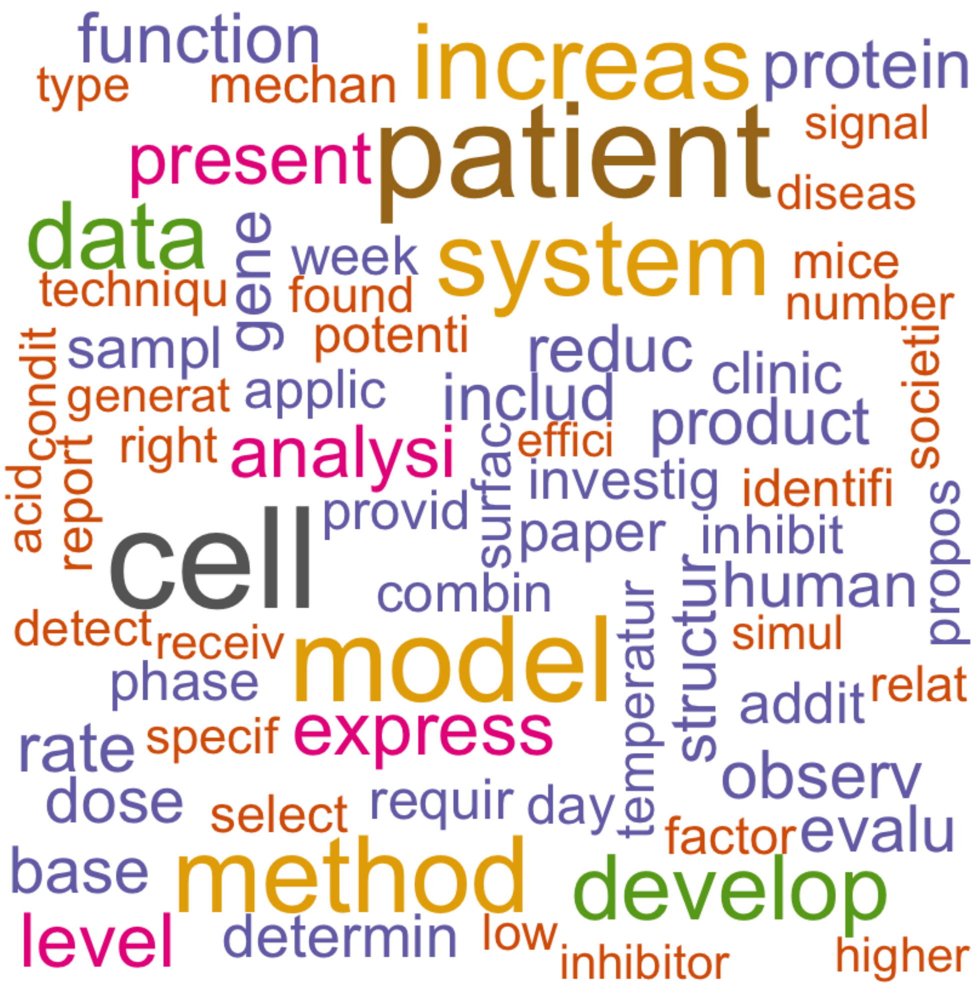


Table 11. Summary Statistics of Publication-IPO Dataset

This table displays summary statistics of the scientific article publications of firms from three years before to five years after IPO. Section A displays the distribution of scientific publications across 9 major journal fields. Sections B and C show the average innovation measures during 3 years before IPO and during 5 years after IPO, respectively. Section D lists the IPO filings and total scientific publications by year.

Section A – Distribution of scientific publications across 9 major journal fields

	Number of Publications	Percentage
Biochemistry, Genetics and Molecular Biology	2011	30.5%
Chemistry	261	4.0%
Computer Science	363	5.5%
Engineering	726	11.0%
Medicine	542	8.2%
Agricultural and Biological Sciences	202	3.1%
Immunology and Microbiology	224	3.4%
Physics and Astronomy	151	2.3%
Others	2123	32.2%
	6603	100.0%

Section B – Average innovation measures during 3 years before IPO

	Mean	Median	Standard Deviation
Publication Count	5.14	2.00	7.67
Citations	81.82	26.00	199.38
Abstract Novelty Score	0.12	0.08	0.10

Section C – Average innovation measures during 5 years after IPO

	Mean	Median	Standard Deviation
Publication Count	8.97	3.00	17.23
Citations	77.57	28.00	270.64
Abstract Novelty Score	0.08	0.06	0.06

Section D – IPO Filings and Scientific Publications by Year

Year	IPO Filing	Scientific Publications
1980	0	0
1981	1	0
1982	0	1
1983	1	5
1984	0	27
1985	1	58
1986	11	59
1987	42	68
1988	20	77
1989	12	82
1990	11	122
1991	45	185
1992	50	165
1993	65	191
1994	55	342
1995	72	409
1996	84	559
1997	56	577
1998	49	513
1999	63	573
2000	84	496
2001	6	544
2002	1	363
2003	4	344
2004	25	302
2005	16	224
2006	9	60
2007	3	72
2008	0	64
2009	0	75
2010	0	26
2011	0	13
2012	0	7
2013	0	0
	786	6603

Table 12. Within-Firm Change in Publication Count around IPO

This table shows the changes in scientific publication count around IPO. I use the natural logarithm of the publication count to reduce skewness in the data. To avoid any zero values, I add one to the publication count when taking the natural logarithm. The regression in Column (1) only considers IPO status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-IPO status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets. In the output of the regression analysis, the interaction items are omitted because they have been dropped by the model due to rank deficiency.

	Log Publication Count		
	(1)	(2)	(3)
IPO-3	−0.294*** (0.077)	−0.266*** (0.077)	−0.187 (0.218)
IPO-2	−0.197*** (0.074)	−0.183** (0.074)	−0.102 (0.100)
IPO-1	−0.157** (0.065)	−0.146** (0.065)	−0.097 (0.073)
IPO+1	0.023 (0.059)	0.026 (0.059)	0.020 (0.061)
IPO+2	0.094 (0.059)	0.091 (0.058)	0.120* (0.062)
IPO+3	0.147** (0.058)	0.145** (0.058)	0.205*** (0.063)
IPO+4	0.151*** (0.058)	0.144** (0.058)	0.172*** (0.064)
IPO+5	0.214*** (0.059)	0.204*** (0.059)	0.214*** (0.065)
Industry Concentration (HHI)		−1.198*** (0.324)	−0.498 (0.379)
Turbulence		0.554*** (0.183)	0.635*** (0.211)
Geographic Concentration (EGI)		−0.037 (0.048)	0.022 (0.050)
Log Total Assets			0.075*** (0.017)
Net Income / Total Assets			0.076 (0.054)
Cash / Total Assets			0.572*** (0.086)
RD / Total Assets			0.590*** (0.096)
Constant	1.366*** (0.050)	1.482*** (0.061)	0.696*** (0.128)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	2,391	2,390	1,909
Log Likelihood	−2,833.062	−2,822.618	−2,264.241
Akaike Inf. Crit.	5,690.123	5,675.235	4,566.482
Bayesian Inf. Crit.	5,759.477	5,761.921	4,672.014

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include IPO Status
(2) Includes IPO Status, HHI, Turbulence, EGI, and interactions
(3) Includes IPO Status, HHI, Turbulence, EGI, interactions, and financials

Table 13. Within-Firm Change in Collaborator Count around IPO

This table shows the changes in research collaborator count (number of collaborators/co-authors of each paper) around IPO. I use the natural logarithm of the collaborator count to reduce skewness in the data. To avoid any zero values, I add one to the collaborator count when taking the natural logarithm. The regression in Column (1) only considers IPO status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-IPO status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets. In the output of the regression analysis, the interaction items are omitted because they have been dropped by the model due to rank deficiency.

	Log Average Collaborator Count		
	(1)	(2)	(3)
IPO-3	0.063 (0.075)	0.065 (0.075)	0.288 (0.209)
IPO-2	0.068 (0.071)	0.062 (0.071)	0.093 (0.094)
IPO-1	0.014 (0.062)	0.015 (0.062)	0.071 (0.069)
IPO+1	0.090 (0.056)	0.094* (0.056)	0.101* (0.058)
IPO+2	0.112** (0.056)	0.115** (0.056)	0.133** (0.060)
IPO+3	0.083 (0.056)	0.088 (0.056)	0.138** (0.060)
IPO+4	0.127** (0.057)	0.131** (0.057)	0.169*** (0.061)
IPO+5	0.148** (0.059)	0.152*** (0.059)	0.213*** (0.063)
Industry Concentration (HHI)		−0.519* (0.287)	−0.181 (0.329)
Turbulence		0.398** (0.185)	0.500** (0.212)
Geographic Concentration (EGI)		0.007 (0.043)	0.023 (0.045)
Log Total Assets			0.027* (0.015)
Net Income / Total Assets			−0.077 (0.050)
Cash / Total Assets			0.418*** (0.076)
RD / Total Assets			0.024 (0.087)
Constant	0.697*** (0.064)	0.747*** (0.070)	0.347*** (0.120)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	2,391	2,390	1,909
Log Likelihood	−2,624.318	−2,621.722	−2,088.501
Akaike Inf. Crit.	5,272.636	5,273.444	4,215.001
Bayesian Inf. Crit.	5,341.990	5,360.130	4,320.534

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include IPO Status
(2) Includes IPO Status, HHI, Turbulence, EGI, and interactions
(3) Includes IPO Status, HHI, Turbulence, EGI, interactions, and financials

Table 14. Within-Firm Change in Citation Count around IPO

This table shows the changes in average publication citation count around IPO. I use the natural logarithm of the average citation count to reduce skewness in the data. To avoid any zero values, I add one to the average citation count when taking the natural logarithm. The regression in Column (1) only considers IPO status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-IPO status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets. In the output of the regression analysis, the interaction items are omitted because they have been dropped by the model due to rank deficiency.

	Log Average Citation Count		
	(1)	(2)	(3)
IPO-3	−0.004 (0.147)	0.045 (0.147)	0.017 (0.387)
IPO-2	−0.007 (0.137)	0.007 (0.138)	0.001 (0.174)
IPO-1	0.062 (0.124)	0.078 (0.124)	0.131 (0.133)
IPO+1	−0.019 (0.113)	−0.021 (0.113)	0.006 (0.113)
IPO+2	0.027 (0.110)	0.031 (0.110)	0.067 (0.113)
IPO+3	−0.055 (0.108)	−0.052 (0.109)	0.049 (0.112)
IPO+4	−0.082 (0.110)	−0.088 (0.110)	−0.007 (0.115)
IPO+5	0.031 (0.110)	0.018 (0.110)	0.035 (0.116)
Industry Concentration (HHI)		−1.373** (0.571)	−0.710 (0.630)
Turbulence		1.167*** (0.337)	1.028*** (0.360)
Geographic Concentration (EGI)		−0.0004 (0.078)	0.047 (0.078)
Log Total Assets			−0.006 (0.029)
Net Income / Total Assets			−0.068 (0.091)
Cash / Total Assets			1.067*** (0.146)
RD / Total Assets			0.247 (0.159)
Constant	3.114*** (0.094)	3.226*** (0.112)	2.587*** (0.222)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,799	1,799	1,454
Log Likelihood	−2,979.490	−2,971.123	−2,356.499
Akaike Inf. Crit.	5,982.980	5,972.247	4,750.999
Bayesian Inf. Crit.	6,048.920	6,054.672	4,851.358

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include IPO Status
(2) Includes IPO Status, HHI, Turbulence, EGI, and interactions
(3) Includes IPO Status, HHI, Turbulence, EGI, interactions, and financials

Table 15. Within-Firm Change in Novelty Score around IPO

This table shows the changes in average novelty score around IPO. The regression in Column (1) only considers IPO status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-IPO status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets.

	Firm-Level Novelty Score		
	(1)	(2)	(3)
IPO-3	0.040*** (0.013)	0.047*** (0.016)	0.018 (0.035)
IPO-2	0.013 (0.011)	0.021 (0.015)	0.022 (0.018)
IPO-1	0.028*** (0.010)	0.035*** (0.013)	0.045*** (0.015)
IPO+1	0.0002 (0.009)	−0.00004 (0.009)	0.001 (0.008)
IPO+2	−0.017* (0.009)	−0.017* (0.009)	−0.018** (0.008)
IPO+3	−0.023*** (0.009)	−0.023*** (0.009)	−0.023*** (0.009)
IPO+4	−0.014* (0.008)	−0.014* (0.008)	−0.018** (0.008)
IPO+5	−0.027*** (0.008)	−0.028*** (0.008)	−0.029*** (0.008)
Industry Concentration (HHI)		−0.076 (0.082)	−0.122 (0.117)
Turbulence		−0.071 (0.055)	−0.145* (0.083)
Geographic Concentration (EGI)		−0.037 (0.035)	−0.094** (0.044)
Log Total Assets			0.002 (0.002)
Net Income / Total Assets			−0.002 (0.007)
Cash / Total Assets			0.010 (0.010)
RD / Total Assets			0.002 (0.012)
Post-IPO * HHI		0.066 (0.090)	0.135 (0.119)
Post-IPO * Turbulence		0.062 (0.062)	0.140 (0.087)
Post-IPO * EGI		0.034 (0.036)	0.092** (0.045)
Constant	0.108*** (0.016)	0.109*** (0.016)	0.090*** (0.019)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	860	860	709
Log Likelihood	1,149.555	1,135.716	954.745
Akaike Inf. Crit.	−2,275.111	−2,235.431	−1,865.489
Bayesian Inf. Crit.	−2,218.028	−2,149.807	−1,765.085

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include IPO Status
(2) Includes IPO Status, as well as HHI, Turbulence, EGI, and interactions
(3) Includes IPO Status, HHI, Turbulence, EGI, interactions, and financials

Table 16. Summary Statistics of Publication-M&A Dataset

This table displays summary statistics of the scientific article publications of firms from three years before to five years after M&A transactions. Section A displays the distribution of scientific publications across 9 major journal fields. Sections B and C show the average innovation measures during 3 years before M&A and during 5 years after M&A, respectively. Section D lists the M&A transactions and total scientific publications by year.

Section A – Distribution of scientific publications across 9 major journal fields

	Number of Publications	Percentage
Biochemistry, Genetics and Molecular Biology	1103	21.2%
Chemistry	251	4.8%
Computer Science	682	13.1%
Engineering	882	16.9%
Medicine	499	9.6%
Agricultural and Biological Sciences	199	3.8%
Immunology and Microbiology	159	3.0%
Physics and Astronomy	116	2.2%
Others	1324	25.4%
	5215	100.0%

Section B – Average innovation measures during 3 years before M&A

	Mean	Median	Standard Deviation
Publication Count	15.21	5.00	29.84
Citations	66.10	23.00	165.96
Abstract Novelty Score	0.08	0.06	0.07

Section C – Average innovation measures during 5 years after M&A

	Mean	Median	Standard Deviation
Publication Count	19.18	6.00	45.73
Citations	68.72	23.00	327.14
Abstract Novelty Score	0.06	0.05	0.04

Section D – M&A Deals and Scientific Publications by Year

Year	M&A Deals	Scientific Publications
1980	0	0
1981	0	1
1982	1	0
1983	3	1
1984	0	0
1985	0	1
1986	1	1
1987	0	4
1988	1	4
1989	3	5
1990	3	18
1991	7	25
1992	16	16
1993	13	30
1994	27	61
1995	11	71
1996	12	144
1997	32	237
1998	35	228
1999	50	316
2000	74	349
2001	38	446
2002	24	374
2003	26	360
2004	19	368
2005	28	335
2006	29	433
2007	22	292
2008	11	328
2009	2	277
2010	0	208
2011	0	150
2012	0	74
2013	0	39
2014	0	19
2015	0	0
	488	5215

Table 17. Within-Firm Change in Publication Count around M&A

This table shows the changes in scientific publication count around M&A. I use the natural logarithm of the publication count to reduce skewness in the data. To avoid any zero values, I add one to the publication count when taking the natural logarithm. The regression in Column (1) only considers M&A status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-M&A status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets. In the output of the regression analysis, the interaction items are omitted because they have been dropped by the model due to rank deficiency.

	Log Publication Count		
	(1)	(2)	(3)
MA-3	−0.061 (0.066)	−0.084 (0.066)	−0.002 (0.076)
MA-2	0.049 (0.063)	0.036 (0.063)	0.112 (0.072)
MA-1	0.046 (0.060)	0.035 (0.060)	0.082 (0.071)
MA+1	0.076 (0.059)	0.071 (0.059)	0.111 (0.071)
MA+2	0.043 (0.060)	0.044 (0.060)	0.039 (0.074)
MA+3	0.071 (0.060)	0.072 (0.060)	0.092 (0.077)
MA+4	0.042 (0.064)	0.058 (0.064)	0.003 (0.085)
MA+5	0.062 (0.066)	0.078 (0.065)	0.094 (0.094)
Industry Concentration (HHI)		−2.142*** (0.634)	−0.489 (0.940)
Turbulence		0.605** (0.298)	0.771* (0.405)
Geographic Concentration (EGI)		−0.216*** (0.080)	−0.070 (0.119)
Log Total Assets			0.207*** (0.029)
Net Income / Total Assets			0.203** (0.083)
Cash / Total Assets			0.083 (0.157)
RD / Total Assets			0.522*** (0.188)
Constant	1.445*** (0.093)	1.673*** (0.112)	0.277 (0.258)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,990	1,990	1,219
Log Likelihood	−2,194.390	−2,189.057	−1,353.314
Akaike Inf. Crit.	4,412.780	4,408.115	2,744.628
Bayesian Inf. Crit.	4,479.930	4,492.053	2,841.638

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include MA Status
(2) Includes MA Status, HHI, Turbulence, EGI, and interactions
(3) Includes MA Status, HHI, Turbulence, EGI, interactions, and financials

Table 18. Within-Firm Change in Collaborator Count around M&A

This table shows the changes in research collaborator count (number of collaborators/co-authors of each paper) around M&A. I use the natural logarithm of the collaborator count to reduce skewness in the data. To avoid any zero values, I add one to the collaborator count when taking the natural logarithm. The regression in Column (1) only considers M&A status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-M&A status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets. In the output of the regression analysis, the interaction items are omitted because they have been dropped by the model due to rank deficiency.

	Log Average Collaborator Count		
	(1)	(2)	(3)
MA-3	−0.119 (0.076)	−0.107 (0.075)	−0.105 (0.082)
MA-2	−0.075 (0.072)	−0.069 (0.072)	−0.103 (0.078)
MA-1	0.014 (0.069)	0.016 (0.069)	0.055 (0.077)
MA+1	0.139** (0.068)	0.140** (0.068)	0.065 (0.078)
MA+2	0.120* (0.069)	0.119* (0.069)	0.097 (0.080)
MA+3	0.137** (0.069)	0.144** (0.069)	0.099 (0.084)
MA+4	0.007 (0.073)	0.014 (0.073)	−0.073 (0.093)
MA+5	0.110 (0.075)	0.103 (0.074)	−0.035 (0.102)
Industry Concentration (HHI)		−0.612 (0.624)	−2.078** (0.844)
Turbulence		−0.804** (0.336)	−0.600 (0.433)
Geographic Concentration (EGI)		−0.261*** (0.083)	−0.724*** (0.120)
Log Total Assets			−0.009 (0.026)
Net Income / Total Assets			0.058 (0.086)
Cash / Total Assets			0.230 (0.155)
RD / Total Assets			0.310 (0.194)
Constant	1.105*** (0.087)	1.173*** (0.111)	1.157*** (0.250)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,990	1,990	1,219
Log Likelihood	−2,391.344	−2,383.186	−1,396.023
Akaike Inf. Crit.	4,806.688	4,796.371	2,830.046
Bayesian Inf. Crit.	4,873.838	4,880.310	2,927.056

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include MA Status
(2) Includes MA Status, HHI, Turbulence, EGI, and interactions
(3) Includes MA Status, HHI, Turbulence, EGI, interactions, and financials

Table 19. Within-Firm Change in Citation Count around M&A

This table shows the changes in average publication citation count around M&A. I use the natural logarithm of the average citation count to reduce skewness in the data. To avoid any zero values, I add one to the average citation count when taking the natural logarithm. The regression in Column (1) only considers M&A status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-M&A status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets. In the output of the regression analysis, the interaction items are omitted because they have been dropped by the model due to rank deficiency.

	Log Average Citation Count		
	(1)	(2)	(3)
MA-3	0.174 (0.121)	0.159 (0.121)	0.133 (0.121)
MA-2	0.093 (0.115)	0.090 (0.115)	0.111 (0.112)
MA-1	0.073 (0.109)	0.068 (0.110)	0.040 (0.110)
MA+1	0.227** (0.110)	0.220** (0.110)	0.246** (0.115)
MA+2	0.115 (0.110)	0.112 (0.110)	0.108 (0.116)
MA+3	0.115 (0.113)	0.106 (0.114)	0.062 (0.124)
MA+4	0.134 (0.116)	0.128 (0.117)	0.396*** (0.132)
MA+5	0.248** (0.118)	0.245** (0.118)	0.407*** (0.146)
Industry Concentration (HHI)		−0.037 (0.940)	0.314 (1.324)
Turbulence		0.962* (0.536)	0.249 (0.651)
Geographic Concentration (EGI)		0.014 (0.125)	0.305 (0.197)
Log Total Assets			−0.084** (0.041)
Net Income / Total Assets			0.079 (0.118)
Cash / Total Assets			0.818*** (0.241)
RD / Total Assets			0.815*** (0.267)
Constant	2.866*** (0.115)	2.854*** (0.150)	2.988*** (0.378)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,297	1,297	786
Log Likelihood	−1,926.102	−1,924.904	−1,058.571
Akaike Inf. Crit.	3,876.204	3,879.809	2,155.142
Bayesian Inf. Crit.	3,938.218	3,957.326	2,243.814

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include MA Status
(2) Includes MA Status, HHI, Turbulence, EGI, and interactions
(3) Includes MA Status, HHI, Turbulence, EGI, interactions, and financials

Table 20. Within-Firm Change in Novelty Score around M&A

This table shows the changes in average novelty score around M&A. The regression in Column (1) only considers M&A status dummies. Column (2) adds industry metrics, including sales concentration (HHI), turbulence, and geographic concentration (EGI), as well as their interactions with post-M&A status. Column (3) adds four additional variables on financial metrics: log total assets, net income / total assets, cash / total assets, and R&D / total assets.

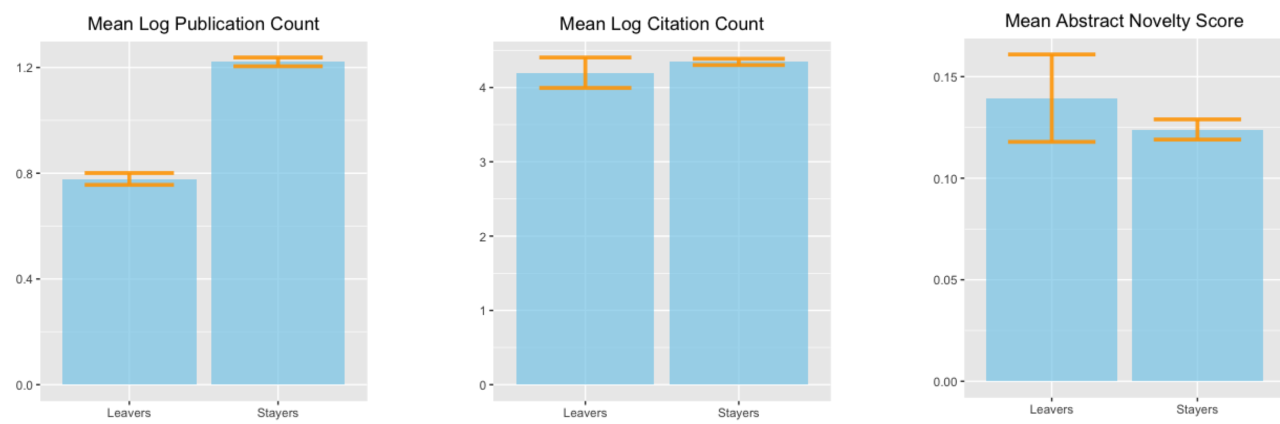
	Firm-Level Novelty Score		
	(1)	(2)	(3)
MA-3	0.020*** (0.005)	0.023*** (0.007)	0.033*** (0.009)
MA-2	0.024*** (0.005)	0.026*** (0.007)	0.037*** (0.009)
MA-1	0.013*** (0.004)	0.015** (0.006)	0.026*** (0.008)
MA+1	−0.005 (0.004)	−0.004 (0.004)	−0.005 (0.006)
MA+2	−0.007* (0.004)	−0.007* (0.004)	−0.008 (0.006)
MA+3	−0.006 (0.004)	−0.006 (0.004)	−0.018*** (0.006)
MA+4	−0.010** (0.004)	−0.011** (0.004)	−0.019*** (0.007)
MA+5	−0.013*** (0.004)	−0.013*** (0.004)	−0.023*** (0.007)
Industry Concentration (HHI)		−0.011 (0.071)	−0.009 (0.096)
Turbulence		0.0005 (0.034)	−0.018 (0.040)
Geographic Concentration (EGI)		−0.090*** (0.030)	−0.080** (0.037)
Log Total Assets			0.004 (0.002)
Net Income / Total Assets			0.007 (0.008)
Cash / Total Assets			0.018 (0.013)
RD / Total Assets			0.007 (0.017)
Post-MA * HHI		0.073 (0.061)	0.135* (0.077)
Post-MA * Turbulence		−0.019 (0.041)	−0.008 (0.055)
Post-MA * EGI		0.099*** (0.030)	0.089** (0.036)
Constant	0.105*** (0.017)	0.097*** (0.017)	0.060** (0.030)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,356	1,356	757
Log Likelihood	2,297.378	2,290.783	1,198.559
Akaike Inf. Crit.	−4,570.757	−4,545.566	−2,353.118
Bayesian Inf. Crit.	−4,508.209	−4,451.745	−2,251.272

Note: *p<0.1; **p<0.05; ***p<0.01
(1) Independent variables only include MA Status
(2) Includes MA Status, as well as HHI, Turbulence, EGI, and interactions
(3) Includes MA Status, HHI, Turbulence, EGI, interactions, and financials

Table 21. Innovator Mobility around IPO

This table displays comparisons of mean publication count, mean citation count, and mean novelty score of three types of innovators around IPO. A stayer is an author with at least a single paper before and after the IPO at the same firm; a leaver is an author with at least a single paper at a sample firm before the IPO, and at least a single paper in a different company after the IPO; a newcomer is an author that has at least a single paper after the IPO event at a sample firm, but no papers before, and has at least a single paper at a different firm before the event. Section A displays the comparisons between stayers and leavers during the three years before IPO. Section B displays the comparisons between stayers and newcomers during the five years after IPO.

Section A – Stayers vs. Leavers in pre-IPO years



Section B – Stayers vs. Newcomers in post-IPO years

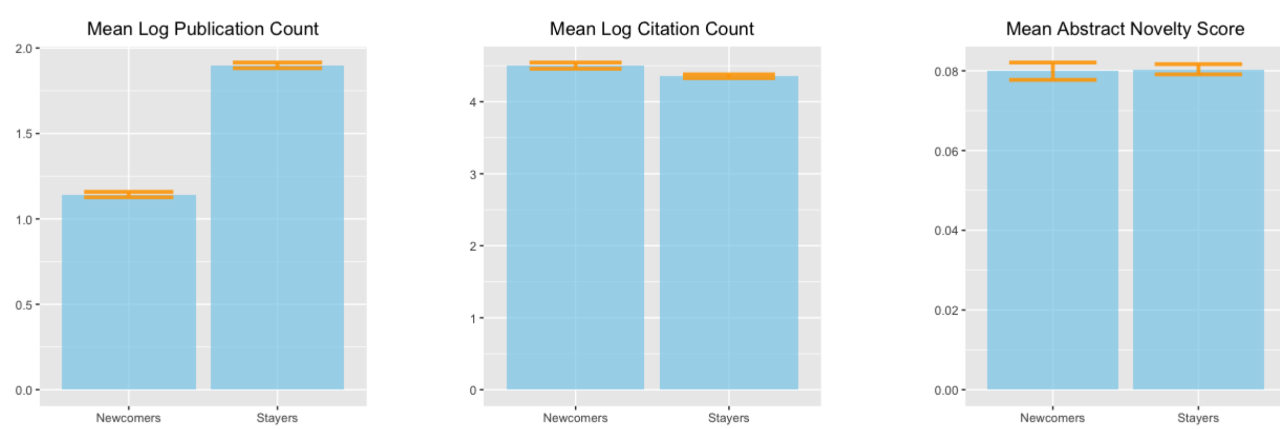
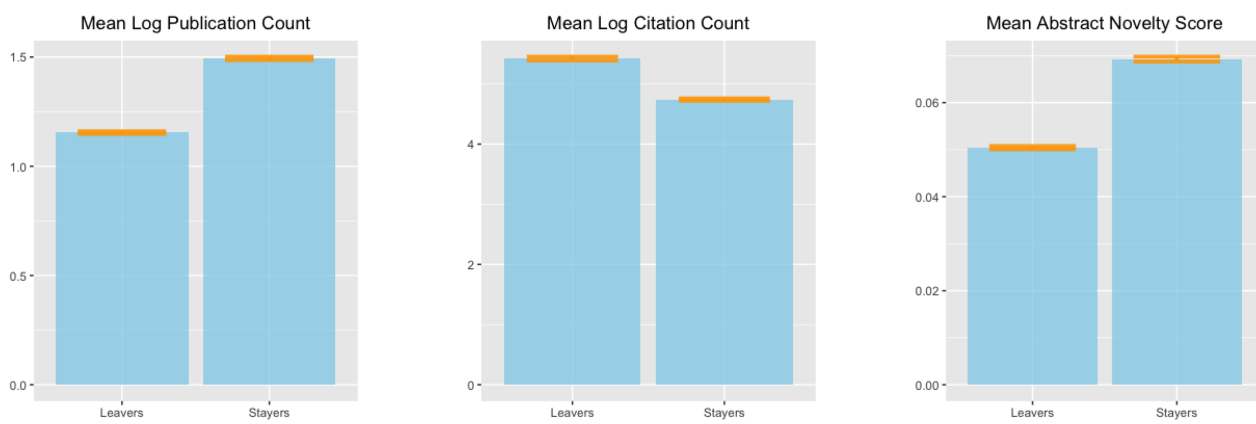


Table 22. Innovator Mobility around M&A

This table displays comparisons of mean log publication count, mean log citation count, and mean novelty score of three types of innovators around M&A. A stayer is an author with at least a single paper before and after the M&A at the same firm; a leaver is an author with at least a single paper at a sample firm before the M&A, and at least a single paper in a different company after the M&A; a newcomer is an author that has at least a single paper after the M&A event at a sample firm, but no papers before, and has at least a single paper at a different firm before the event. Section A displays the comparisons between stayers and leavers during the three years before M&A. Section B displays the comparisons between stayers and newcomers during the five years after M&A.

Section A – Stayers vs. Leavers in pre-M&A years



Section B – Stayers vs. Newcomers in post-M&A years

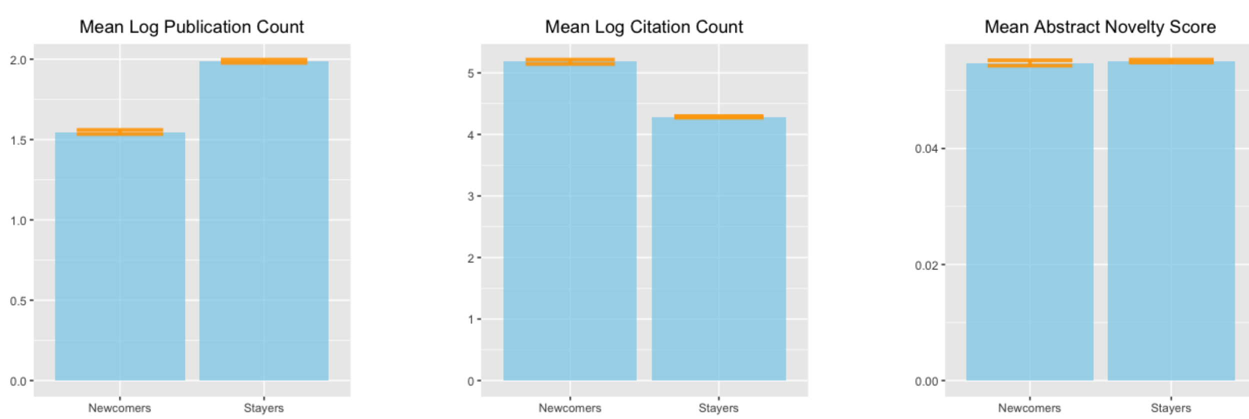


Table 23. Innovation Novelty Score of Cephalon Inc. around IPO

This chart shows the change in innovation novelty score of Cephalon Inc. in years around its 1991 IPO (from 1988 to 1996). The novelty score is calculated based on the average age of non-stop words in the abstract of each article by journal field. The red dashed line indicates that Cephalon went public in year 1991.

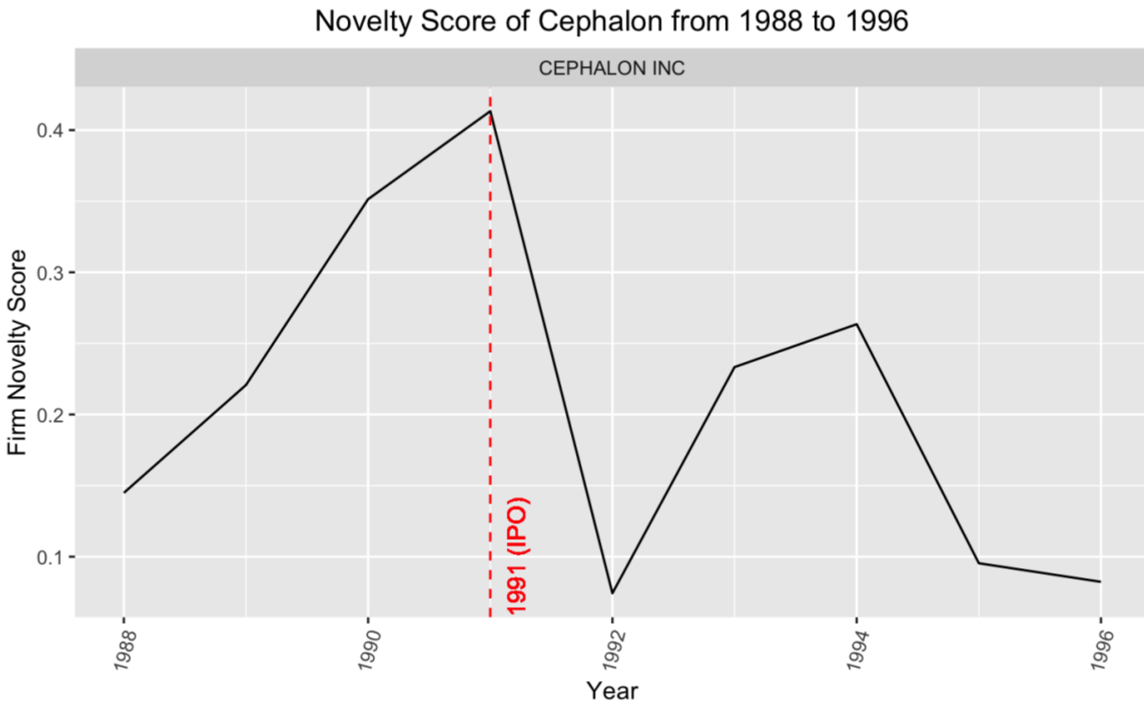


Table 24. Innovation Novelty Score of Hospira Inc. around M&A

This chart shows the change in innovation novelty score of Hospira Inc. in years around its 2006 M&A events (from 2004 to 2011). The novelty score is calculated based on the average age of non-stop words in the abstract of each article by journal field. The red dashed line indicates that Hospira acquired BresaGen Ltd. and Mayne Pharma in 2006.

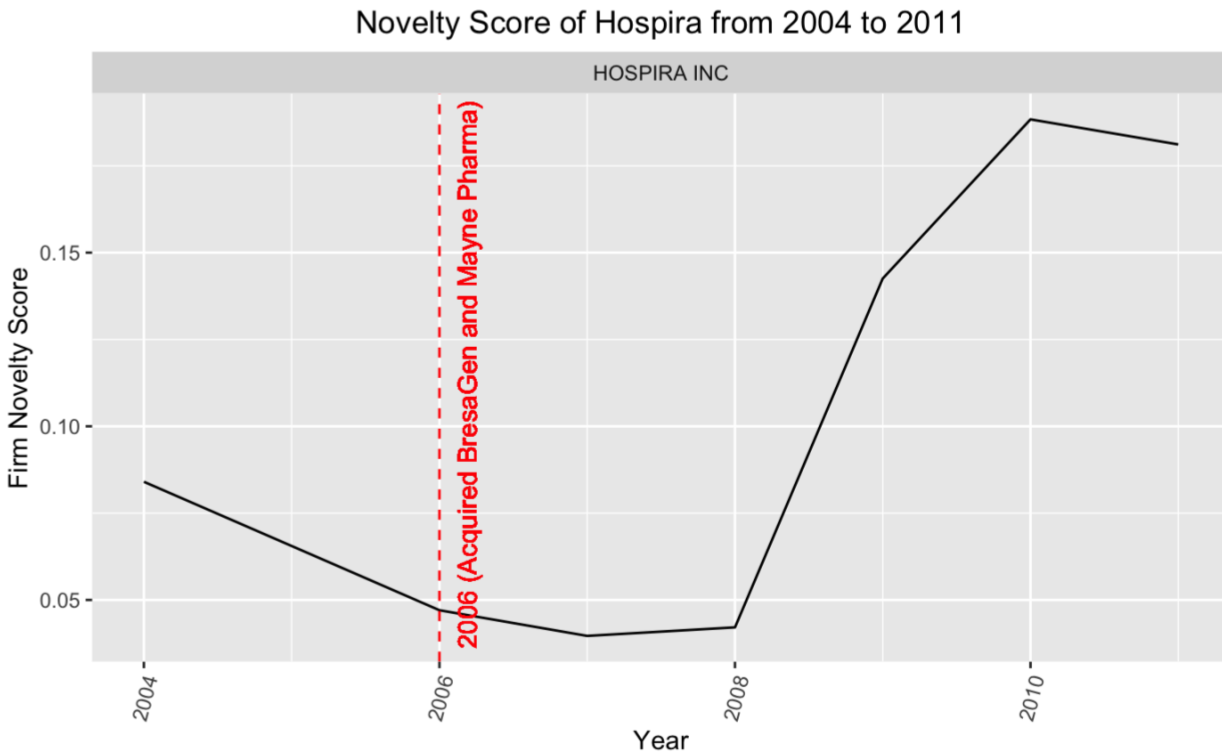


Table 25. Innovation Novelty Score of Eastman Chemical Co. around M&A

This chart shows the change in innovation novelty score of Eastman Chemical Co. in years around its 1999 M&A event (from 1996 to 2004). The novelty score is calculated based on the average age of non-stop words in the abstract of each article by journal field. The red dashed line indicates that Eastman Chemical acquired Lawter International Inc. in 1999.

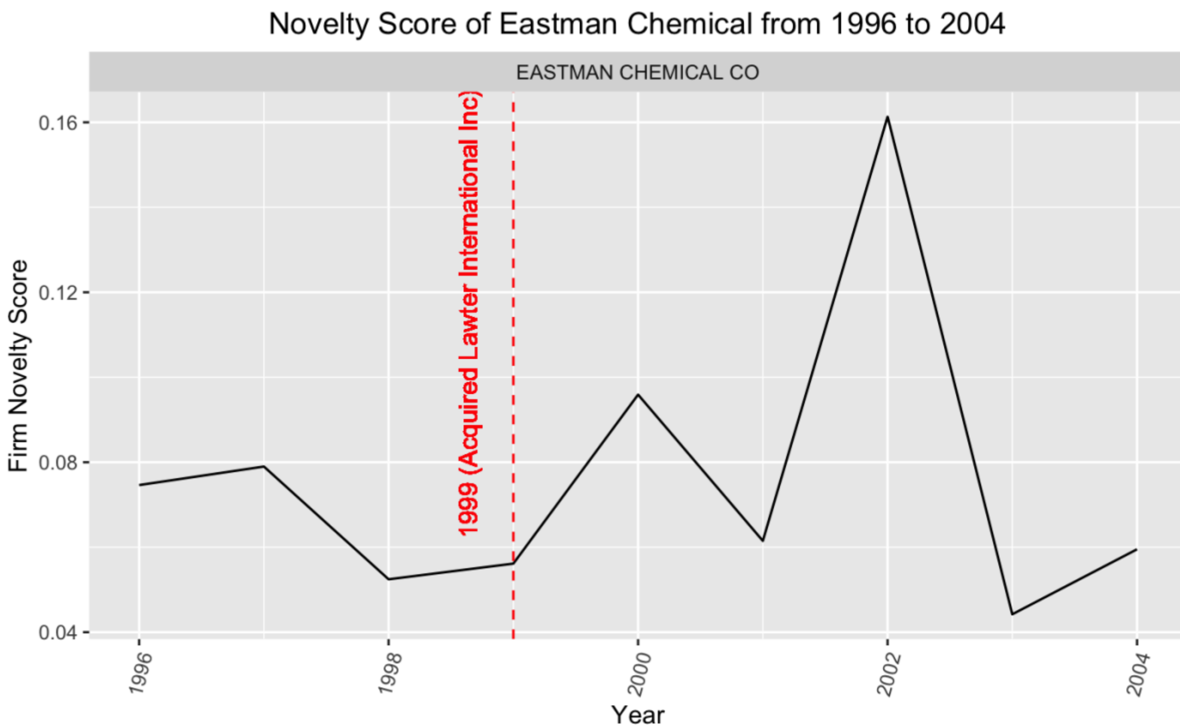


Table 26. Innovation Novelty Score of Millennium Pharmaceuticals Inc. around IPO and M&A

This chart shows the change in innovation novelty score of Millennium Pharmaceuticals Inc. in years around its 1996 IPO event and 1997 M&A event (from 1995 to 2002). The novelty score is calculated based on the average age of non-stop words in the abstract of each article by journal field. The blue dashed line indicates that Millennium Pharmaceuticals went public in 1996. The red dashed line indicates that Millennium Pharmaceuticals acquired ChemGenics Pharmaceuticals Inc. in 1997.