Market Competition and Corporate Innovation Relation:

Revisit and New Insights

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ABSTRACT

I revisit the relation between market competition and innovation. Using patents, citations and R&D as measures for innovation, and text-based metric for competition, I find that firms with higher market power file more patents and receive more future citations, but they do not spend significantly more on R&D. I identify two possible channels to explain the relation: First, the innovative strategies for firms of higher market competency are more exploitative rather than explorative, and they focus on more familiar and crowed areas of technology. Second, I provide evidence that firm's takeover activities could affect firm's innovation incentives, and it is competition environment depended. The innovative incentives by firms with low market competency are greatly disrupted by their takeovers activities, and these firms decelerate their novel projects after major acquisitions, while high market power firms' innovative efforts are more immune to takeovers. Evidence from the inventor-level substantiates the difference. Finally, this study further finds that firms generally acquire targets with similar competition levels.

Keywords: Market competition, Innovation, Research and Development, Merges and Acquisitions
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I. Introduction

THERE HAS BEEN a vast number of literature investigating the impact of product market competition on corporate innovation. Among them, Schumpeter (1942) asserts a negative relation between competition and innovation. Since then, later empirical studies have been quite contentious over the relationship and there is little empirical support for the Schumpeterian view that large firm size or high market power is associated with higher level of innovative activities: Scherer (1967) documents an inverted-U relation between competition and innovation in an analysis of Fortune 500 firms. Nickell (1996) and Blundell, Griffith, and Van Reenen (1999) return to the linear model and find a positive relation. Whereas Aghion, Bloom, Blundell, Griffith, and Howitt (2005) document an inverted-U relation by data from U.K.

The controversial relation between market competition and innovation could be attributed to several reasons. For example, differences in measures of market competition, discrepancies in the gauges of innovation, variances on estimation methodology and sampling. Prior studies use measures like market concentration, profit margin, import penetration etc., as metrics of competition, and though most of them are not accurate metrics for the degree of competition (see Ahn, 2002, for a review). The imperfections of these market structure measures stem from the facts that some of them are industry-level measures, where the industry boundaries in official data are sometimes inappropriate to capture the market territories that firms actually compete against, or they fail to capture dynamic aspects of competition such as future entrants, or they may overlook competition from private sectors.

This study uses a novel competition measure borrowing from more recent literature, i.e., the 10-K Text-based network industry classification concentration index, or TNIC-HHI, by Hoberg and Phillips (2015). This measure allows us to overcome the drawbacks that traditional measures could bear. The new industry classification system (TNIC) is based on product descriptions from annual firm 10-K filings with the Securities and Exchange Commission (SEC) and it is updated every year. The TNIC-HHIs are customized to each firm, since every firm has its unique set of rivals, which are identified by web crawling and text parsing algorithms to calculate similarities of firms' business descriptions. Hoberg and Phillips (2015) view the TNIC industries to be far more informative and useful than Fixed Industry Classification (FIC) system like SIC and NAICS, and they use this new classification system to show its advantage at explaining the cross-section of firm characteristics.

Using patent- and citation-based metrics for innovation outputs and R&D expenditure as measure for innovation inputs, I first revisit the relation between market competition and corporate innovation. The cross-sectional result indicates an increasing relation between firms' patenting activities, patent's related citations and the new market concentration measure (TNIC-HHI), and a decreasing relation between R&D expenditures and TNIC-HHI. Controlling for the firm fixed effect leads to no significant relation between R&D and TNIC-HHI. The discovered relations echo prior literature (Blundell et al., 1999, etc.) that innovation and competition could be linear. More importantly, this study is in no attempt to join the debate for the contentious relation, rather, it seeks to find alternative explanations which deviate from prior studies.

The divergent relations for innovation inputs and outputs prompt us to think the underlying mechanisms. One possible explanation is that firms with higher market power could work more efficiently in innovation, that is, they could generate more patentable products at lower costs. However, it is also likely that firms could focus on previously proven trajectories in innovation and exploit deeply on the well-known technologies, rather than explore on new and riskier technologies (March, 1991).

Apart from simple patent counts, which raise increasing concern in recent innovation research (see the argument by Lerner and Seru, 2014), I follow Balsmeier, Fleming, and Manso (2017) to calculate a suite of nuanced innovation measures, to explore their relation with competition. I find that firms with higher TNIC-HHI to have more backward and self-citations, and their patents generally focus on more familiar and crowed areas of technology. Also, the citations are mainly from patents that sitting in the middle of the citation distribution, rather than uncited as well as breakthrough patents (highly cited), both of which are associated with riskier innovative efforts. In this regard, the evidence suggests that high TNIC-HHI firm roll out more patents by exploitation of their existing portfolios, which could be at lower cost when compared with exploration trajectory of innovation.

Another possible explanation toward the innovation and competition relation comes from the Mergers and Acquisitions (M&A) theory. When breaking the sample into acquirer and non-acquirer subsample, I find that the increasing relation between TNIC-HHI and innovation is mainly driven by the bidding companies. More recently, literature starts to shed light on the mechanisms for enhancing innovation beyond organic R&D spending (Sevilir and Tian, 2012; Phillips and Zhdanov, 2013, among others). These studies reveal that firms may acquire innovation from outside the firm boundaries to supplement their in-house development efforts. In this regard, mergers and acquisitions (M&A) become an important channel for firms to enhance their competency in innovation. This study seeks to mingle market competition, corporate innovation with the theory of mergers and acquisitions. I present evidence that mergers and acquisitions activity could be one of the important forces that shape the competition and innovation relation. To be more specific, my empirical results reveal that firm's patenting activities could decelerate on average after acquisitions, but the decline in number of newly applied patents as well as citations in the post-merger periods is mostly concentrated in firms from low market concentration group, whereas firms located in high market concentration group are moderate in this change. This uneven impacts on future innovation from the takeover market suggest that firms of smaller market power are as if, bearing the most brunt from M&A regarding their innovation activities, and firms of higher market power are relatively more "immune" to their takeovers. Therefore, this study reveals that "acquisitions could hurt innovation", at least in a short-run period after mergers for some firms, in some way.

After documenting the suggestive evidence that M&A could play a role in market competition and innovation relation, I then use a quasi-experiment to estimate the treatment effect of the M&A on post-merger innovation outputs for firms with different market competitiveness, to reassure my findings. Following Seru (2014) and Bena and Li (2014), I involve a sample of withdrawn bidding attempts to estimate the treatment effect. I show that firms from the low market competency group with successful takeovers suffer a drop in their post-merger innovation output, while acquirers with failed biddings decrease even more steeply than successful bidders. What is more importantly, my results reveal that the treatment effect (drop in post-merger patenting activities) is not pronounced in high market concentration group. This finding highlights that M&A could adversely affect the innovative incentives of companies, and the magnitude of takeover activities' impacts on firms' patenting behaviors could be competition-environment-depended.

To explore the underlying mechanism of the different magnitude in effects brought by mergers. I then follow Seru (2014) and Bernstein (2015) to investigate the issue at firm's inventor-level around mergers. I find that inventors from the high market group to have a higher likelihood to be retained at the original firms, while the low market competency firms suffer inventor exodus in the post-merger periods. Stayers in the high competency firms produce more patents after mergers than stayers from the low market firms. Moreover, I find that inventors who left original employers and employed by a new firm get their productivity enhanced in the post-merger period, especially when the inventor leaving from a low market firm and later joining a high market firm. The combined effect indicates that firms of low market competency are less strong regarding innovative elites in the post-merger periods than firms of high market competency, which in result, dent their post-merger innovation activities. Different from Seru (2014), this is the first empirical study to examine the inventor's mobility from the buyer's side in M&A in detail, to my best knowledge.

It is also interesting to know what drives firms of low competency to have relatively more R&D spending but be less engaged in patenting activities. It could be explained by recent literature (Phillips and Zhdanov, 2013, among others) that smaller firms burn heavily in R&D in order to turn themselves into ideal targets for future takeovers. In other words, these low market power firms spend heavily in their own labs, not only for the purpose of survival in product market, but also for the expectation that they could be sold entirely in the takeover market. My empirical results verify that these firms are more likely to be targeted in later years, and they are most likely to be acquired by firms from low market concentration group, i.e., from similar competition environment, who spends more in R&D but generates less patents. Similarly, I find that firms from other different market concentration quintiles are most likely to be acquired by bidders with similar competition-levels. As such, it reveals a new dimension of pairing issue in M&A, the "like-buys-like" matching pattern.

This study contributes to several strands of literature. First, I revisit the contentious relationship between market competition and innovation. Recent papers on innovation (Fang, Tian, and Tice, 2014; Chemmanur, Loutskina, and Tian, 2014, for example) widely cite the non-linear relation from Aghion et al. (2005), though their study stands at the industry level. Still, in these innovation studies, the non-linear control of market competition (industry-level HHI) turns out not stable to takes effect, and it seems that adding the competition measure as extra control is more symbolic than practical. This research goes into the relation at the firm level and finds a significant and robust relation between competition and innovation, which could help us understand the heterogeneity of innovation within industries.

Second, I take heed of the critiques of Lerner and Seru (2014), and follow Balsmeier, Fleming, and Manso (2017) to construct a battery of nuanced innovation measures. These measures provide new and unique insights, which beyond the simple patent and citation counts, into the dividing innovative strategies of different firms. The evidence reveal that high TNIC-HHI firms could boost their innovation portfolio through exploiting its current arena of expertise.

What's more, the well-established theories in M&A enable me to think about whether corporate takeovers could in play at forming the relations. Therefore, my paper also contributes to the growing line of "acquiring innovation" literature (see, Sevilir and Tian, 2012; Bena and Li, 2014; and Phillips and Zhdanov, 2013, etc.). Aghion and Tirole (1994) argue that firms with lower ability in innovation may acquire targets of higher ability in innovation, since it is more efficient to acquire than to. Phillips and Zhdanov (2013) find that the market of M&A indeed prompts firms to conduct R&D, especially for small firms, and the reason why larger firms are less willing to engage in the "R&D race" with small firms is that they may feel better to obtain innovation through acquisitions rather than develop by themselves. Sevilir and Tian (2012) find that there is a positive relation between the acquisition activities of a firm and its future innovation outcomes. Bena and Li (2014) discuss the pairing issue of merges and acquisitions from the innovation prospective and find that acquirers with high patent portfolio but low R&D expenditures tend to acquire targets of high R&D but with low growth of patent applications. My study documents the evidence that high market concentration bidders generally acquire firms of high market concentration while low market concentration acquirers generally acquire firms of low market concentration, a “like-buys-like” pattern. Also, Higgins and Rodriguez (2006) reveal that outsourcing R&D activities could be utilized by firms to replenish their innovation pipelines in pharmaceutical industry. My study also finds that these R&D intensive firms are more likely to be targeted in later periods. Further, I show that firms with high market competency acquire human capital in their mergers, while firms with low market competency lose their human resources after mergers.

Further, while Bena and Li (2014) document some trivial evidence that firms may generate less patents in post-merger period, my study echoes the findings of them and I go a step further to find that the drops in patenting activities in the post-merger periods are mostly by firms of low market competency. Different from Seru (2014), which is quite related to my study and documents the evidence that firms acquired in diversifying mergers produce less innovation in the post-deal periods, my study will focus on acquirer’s side, and I drill further to examine whether the “hurts” on innovation are evenly spread over acquirers of different market power in product markets. That is, I ask which type of firm could be more vulnerable to the disruption of takeovers. Finally, my paper is related to Bernstein (2015) and Seru (2014), who explore the underling mechanism in innovation by investigating the data from the inventor-mobility angle. The exodus of human capitals and productivity change of retained inventors after mergers provides unique insights into why the number of filing patents could drop in the post-merger periods for certain firms.

The rest of the paper is organized as follows. Section 2 reviews literature on competition, innovation and takeover issues. Section 3 develops the hypotheses. Section 4 discusses the sample and data. Section 5 presents the empirical research outcomes. Section 6 concludes.

II. Literature Review

A. Competition and Innovation

Motivated by Schumpeter's conjecture that large firms in more concentrated markets have advantage in innovation, many empirical studies have delved into the relation between competition and innovation, and various theories are provided on this topic (see, for example, Acs and Audretsch, 1987, 1988; Geroski and Pomroy, 1990; Pavitt, Robson, and Townsend, 1987; Geroski, 1995, etc.). On the one hand, when monopolistic companies are relatively more active in innovation, which due to their deep pockets and less market uncertainty, the increment in competition could reduce their incentives for future innovation, and devote more efforts to projects which would transfer into growth in market share more rapidly, rather than patenting activities which would take years to materialize. While on the other hand, the *Darwinian effect* says that competition could serve as an incentive for incumbent firms to be innovative and introduce new products to fend off competition, and to be more entrenched in the market in future periods.

While Geroski (1990) finds no support in his data for Schumpeterian assertion about the role of monopoly power in stimulating innovation. Scherer (1967) documents an inverted-U relation between competition and innovation in an investigation of Fortune 500 firms. Nickell (1996) returns to the linear model and finds a positive relation. Blundell, Griffith, and Van Reenen (1999) use new estimation methodology to find a positive effect of market share on headcounts of innovations. They also find that when market share is interacted with innovation, the impact on the firm's market value becomes more positive, meaning that high market share firms tended to be benefit more from their innovations. Aghion et al. (1999) argue that intensified market competition could force managers to rev up the adoption of new technologies in order to avoid loss of control rights due to potential bankruptcy risk, which lends support to the view that the *Darwinian effect* could in play to explain why competition could be conducive to innovation.

More recently, Aghion et al. (2005) document an inverted-U shape for competition and innovation. Their model suggests that there are neck-and-neck and leader-and-follower firms in the economy. The increment in market competition will prompt neck-and-neck sectors to increase research intensity while decrease the laggard firm’s incentive to innovate. To explain the rationale of the inverted-U, they argue that the fraction of sectors with neck-and-neck competitors are endogenous given. When competition is low, the *Escape-competition effect* will dominate since a larger equilibrium fraction of sectors involve neck-and-neck firms to compete against incumbents. When competition becomes more intensive, however, a larger fraction of sectors in equilibrium have innovation being introduced by laggard firms, therefore *Schumpeterian effect* will dominate under this circumstance.

Recent papers on innovation (He and Tian, 2013; Fang, Tian, and Tice, 2014; Chemmanur, Loutskina, and Tian, 2014, etc.) widely cite the non-linear relation between competition and innovation from Aghion et al. (2005). However, in these studies, the non-linear control of market competition (industry-level HHI and its squared term) does not seem to persistently capture the market structure in affecting innovation, and it seems that adding the SIC-based concentration measure as extra control is more symbolic than practical.

B. Innovation, Competition and M&A

There are mainly two channels for a firm to expand its innovation portfolios. One is to invent from their own labs. The organic growth in innovation needs intensive investment in R&D and it takes time to turn into products. Whereas another way is through acquisitions.

Aghion and Tirole (1994) argue that firms with lower ability in innovation may acquire targets of higher ability in innovation, since it is more efficient to acquire than to innovate. While Rhodes-Kropf and Robinson (2008) state that M&A can prompt innovation through complementing assets of two parties, and the combined entity is more likely to generate new products and technologies. Consistent with the selection channel propelled by Aghion and Tirole (1994), Sevilir and Tian (2012) find that there is a positive relation between the M&A activity of a firm and its future innovation outcomes. They also find that acquiring targets with existing patents is related with higher value creation, which is manifested by higher abnormal return around the announcement date as well as superior long-term stock performance. Higgins and Rodriguez (2006) use sample from pharmaceutical industry to reveal that bidders are quite successful in converting the target's R&D inputs into their own research outputs.

Moreover, Phillips and Zhdanov (2013) argue that the reason why bigger firms are less willing to compete R&D spending with those small firms is that they are in better position to obtain innovation through M&A rather than develop themselves. This argument also proofs why some firms are less innovative in pre-merger periods but own a lot of innovation portfolios after takeovers. Hoberg and Phillips (2010) use the text-based measure of product similarities among firms to investigate how similarities and competition affect firms' incentive to merge and impact on post-merger outcomes. They find that firms that are more broadly similar to all the firms in the industry are more likely to merge and firms with more similar rivals are less likely to merge. The former finding is referred to as "asset complementary effect" and the latter one is called "competitive effect". For the post-merger outcomes, they find that value is created upon the deal announcement, and the long-term profitability, better sales growth and more product descriptions are achieved when targets are similar to acquirers in products. In Bena and Li (2014), their study delves into the characteristics of the participants of M&A which related to innovation. They find that, innovative firms are more likely to be involved in merger transactions. For innovative firms which have larger innovation portfolio but low R&D expenditures, are more likely to become acquirers. Whereas those have slower growth in innovative output but more R&D investment are more likely to become targets. This evidence indicates that targets could be difficult to convert R&D expenses into patents in some way. Moreover, firms which have more similarities or overlap in their innovation activities tend to be more likely to be paired in the M&A, meaning that the reciprocal relatedness is important to both the acquirers and targets. Their study also documents that the combined innovation output of bidders and targets improves after takeovers, if the two parties have overlap in technologies before acquisitions. In a more related study, Seru (2014) documents the evidence that firms acquired in diversifying mergers produce less innovation in the post-merger periods by conducting a quasi-experiment using both successful and failed biddings. He finds that relative to firms with failed biddings, firms with successful takeovers suffer a significant decline in novelty of their research output after the merger, and he argues that this drop is driven by the change in mobility of inventors around the acquisitions. Different from Seru (2014), my study focuses on the bidders rather than targets.

Finally, my research is also related with Balsmeier, Fleming, and Manso (2017), who find that firms that transition to independent boards lead to more patents and citations, but no significant change in R&D. They posit that the incremental patents focus on more crowed and familiar areas of technology and the citation increase mainly come from patents that in the middle of the citation distribution. Their study get a comprehensive examination of a batch of nuanced innovation metrics, such as backward citations (Lanjouw and Schankerman, 2004), self-citations (Sorensen and Stuart, 2000), new class and unknown class patents to a company, and number of patents ranked by citation distributions (Azoulay, Graff Zivin, and Manso, 2011) etc.

In sum, these theories discussed above, which mix market competition, innovation and acquisitions, prompt me to think possible mechanisms to explain the relation between product market competition and corporate innovation.

III. Hypothesis Development

In this section, I develop hypotheses on the relation between market structure and innovation. Different from the explanations from prior literature (Aghion et al., 1999; Aghion et al., 2005), I underline the dividing innovative strategies for firms of different market power and I also highlight the mergers and acquisitions theory in shaping the relation.

Innovation strategies are not merely related with creating more patents and receiving more citations, they cares a lot about the way, or how, to generate patents. There are two search strategy regarding innovation. One is the exploration of new technologies, and another is exploitation of existing technologies (March, 1991). For firms located in the competitive market, they could roll out some newly and original products to fend off the competition environment. This process generally needs intensive R&D investment and it will be quite risky to generate impactful patents. However, for firms with higher market power and dwell in more comfortable markets, they could focus on exploitation in order to maximize the outcome. In other words, creating breakthrough products could not be imminent for them, which would be much risker, and they could simply boost their innovation portfolio by delving into technologies that they are familiar with. Therefore, this leads to my first hypothesis:

(H1) Firms of low market competency have high R&D expenditure but low patent portfolios and their innovative strategy is more explorative than exploitative. Firms of high market competency have low R&D expenditure but high patent portfolios and their innovative strategy is more exploitative than explorative.

For firms of low competency, which generally focus on limited number of products and walk within limited industries, intensive R&D expenditures could not only help them ward off pressure from competitors, but could also help attract takeover actions from other bidders. Bena and Li (2014) argue that R&D-intensive firms with slow growth in patent output are more likely to be acquired in future periods. High R&D but low patent output growth could mean that the efficiency of transferring R&D into patentable products is low in some way. Phillips and Zhdanov (2013) also posit that small firms are R&D intensive because they want to be acquired by large firms, and successful innovations make them attractive acquisition targets. Exit through strategic sales becomes an important motivation to continue to spend on R&D for these firms. For firms of high competency, they could just buy those research intensive company by exploiting their innovative potential and transfer the R&D inputs more efficiently to patentable products. In this regard, it is nature to think whether the innovation comparative advantage way of pairing in M&A is the same regarding market competency. From another side is the “like-buys-like” matching issues in forming merger pairs in M&A. Hoberg and Phillips (2010) show that, firms with broad product market similarities to all firms in the economy are more likely to merge. Rhodes-Kropf and Robinson (2008) find that paired firms in mergers typically have similar market-to-book ratios. For firms with similar market competency, they could be more likely to form merger pairs either, due to the potentially reciprocal relatedness from their complementary assets in product market.

Thus, I have my second hypothesis:

(H2) Firms of low market competency have high R&D expenditure but low patent portfolios and they are potential targets of future takeovers. Firms of high market competency will have low R&D investment and more patents through acquiring firms with low market power.

Regarding the post-merger innovation behaviors, firms of low market competency could press the brakes on innovation due to engaged post-deal combination process, whereby the innovation creation could be put at second place. But for firms of high market power, given their deep-pocket and well-rooted position in the market, these firms' innovating activities could be more "immune" to the "disruption" of takeovers, and keep their innovative incentives at a stable level.

(H3) Innovative activities for firms of low market competency are greatly disrupted by their takeover activities, leaving them less innovative in the post-merger period. Whereas innovative activities for firms of high market competency are less likely to be disrupted by their takeover activities, leaving their patenting activities resilient.

IV. Sample and Data

A. Sample Construction

My sample consists of all U.S firms that recorded in Compustat/CRSP from year 1996 to 2006. My panel data coverage starts from 1996 since the new measure on firm competitiveness, the TNIC-HHI, starts from 1996. While my data ends in 2006 since the coverage of innovation measures ends in 2006. I drop the data of 1996 since I only use them to create lag data for 1997. I obtain patent and citation information from the

National Bureau of Economic Research (NBER) Patent and Citation database, which has track of the firms' patent and citation information from 1976 through 2006, and I use the NBER bridge file to match the patent information with the firm sample. I get M&A transaction information from Securities Data Company (SDC) Platinum Mergers and Acquisitions database. As with control variables, I collect the firm-level financial information from Compustat, and institutional holdings information from Thomson's 13F database. I restrict that the firms in my sample to have total sales for at least $1 million. I further exclude firms from financial industries (SIC Code 6000-6999).

Following existing literature on innovation (Sevilir and Tian, 2012; Fang, Tian, and Tice, 2014; Chemmanur, Loutskina, and Tian, 2014; Bena and Li, 2014, among others), I use the widely accepted patent and citation-based metrics to measure the company's innovation outputs. The NBER database provides detailed information for each patent as well as its citations, which includes the patent's assignees (usually corporations), the number of citations received by each patent, the patent's technological classification, and the patent's application and grant date etc. The database has a good dynamic matching for each patent and its assignee, and it tracks accurately the belongings of each patent. The database also uses data on mergers and acquisitions of public companies reported in the SDC database to track the changes, and it assumes that when an organization is acquired/merged/spun-off that its patents go to the new owner timely. In this study, I construct two measures, Patent number and Citation number, by following Fang, Tian, and Tice (2014), Chemmanur, Loutskina, and Tian (2014). More specifically, the first measure is the number of patent applications a firm files in a given year and eventually granted. Following existing literature in innovation, I use a patent's application year rather than granting year as the application year since it is more accurate to capture the actual time of innovation for a given firm (Griliches, Pakes, and Hall, 1988). The second measure is the total number of citations received in subsequent years regarding patents filed each year, this measure could reflect the patent's influence, or importance, in a longer horizon. In this way, the two innovation output measures could catch both the quantity and quality of innovative strength of a given firm in a given year.

However, both measures on innovation output suffers truncation problem, as argued in literature (Hall, Jaffe, and Trajtenberg, 2001; 2005). This is because, there is a time lag between a patent application year and grant year (around two years on average), therefore there will be a gradual decrease in number of patent applications that finally granted as we close to the last few years in the sample period. That means, both the patent number count and related-citation number count in the end of my sample period could be under-counted, since the patents applied in years which close to 2006 are still under review and not yet approved by that year. Following Hall, Jaffe, and Trajtenberg (2001, 2005), I correct for the truncation bias in patent counts by multiplying the “weight factors” estimated from the application-grant empirical distribution. Following Hall, Jaffe, and Trajtenberg (2001, 2005), the truncation in citation counts is also corrected by estimating the shape of the citation-lag distribution, and multiple the estimated weight factors with the counted number in database. I set the two variables to zero if the firm has no record in the patent database as in innovation literature (Cornaggia, Mao, Tian and Wolfe, 2015; Fang, Tian and Tice, 2014; Sevilir and Tian, 2012). Finally, since both measures are rightly-skewed, I use the natural logarithm of the truncation-corrected patents and citations number, which denoted by Ln(Patent) and Ln(Citation) respectively, to present the innovative abilities of each firm, and I add one to each values when calculating the natural logarithm for firms without patenting records. For R&D intensity, which serves as measure for innovation inputs, is calculated by R&D expenditure scaled by firm asset. Separating R&D and patents and citations could help us clearly understand the input-output relation in innovation.

Moreover, I deviate from simple patent and citation count and follow Balsmeier, Fleming, and Manso (2017) to calculate a suite of nuanced innovation measures. I hereby give a general description of the way of calculation and the meaning for each of them. I first calculate “Backward-citations”, which is the number of citations that each patent makes to prior patents (Lanjouw and Schankerman, 2004). This measure reflects the current patent in relation with prior technologies so it correlates with the way of search in more crowed and well-known technological areas. Second, the “Self-citations", which is the number of times a given patent cites other patents owned by the same company (Soresen and Stuart, 2000). This measure therefore reflects the degree of which that the inventor search within the firm boundary. Third, the "New-class patents", which is calculated by the number of patents that are filed in technology classes previously unknown to the company, dating back to all the innovation history of the company. The complement is the "Known class patents". The two measures, one measures the explorative efforts and another for exploitative efforts of innovation. Fourth, I categorize patents according to how many citations they have received relative to other patents that filed and later granted in the same technology class and year (Azoulay, Graff Zivin, and Manso, 2011). To accurately position the patent according to the citation distribution, I include all the patents, whatever from public inventors or private inventors into the estimation process. I calculate four categories and assign the patent to one of them: "Top 1%" means the patent falls into the 1% most cited patents within a given technology class and application year. This means that the invention is rather successful and breakthrough. "Top 10%-2%" indicates whether the patent falls into the top 10%-2% cited patents within a three-digit technology class and application year. "Cited patents" means that the patent is cited at least once but do to appear in the top 10% of the citation distribution. "Uncited patents" means that the patent is completed failed regarding the innovation efforts. I aggregate the number of patents categorized by the four bins to firm-year level to reflect the degree of innovation successfulness. I assign these innovation variables to zeros if the firm does not file a patent in that year.

Then, following existing research in M&A, I restrict my M&A sample according to the following criteria: 1) The deal is announced between Jan. 1st, 1996 and Dec. 31st, 2006 and later completed; 2) The acquirer is an U.S public firms and not from financial industries (SIC Code 6000-6999); 3) The deal is in the form of "Merger", "Acquisition of Assets", or "Acquisition of Major Interest"; 4) The transaction size is larger than 1 million and is not a "Repurchase", "Spinoff", "Recapitalization", "Self-tender" or "Privatization"; 5) The bidder owns less than 50% of the target before the transaction and larger than 50% after the transaction. This filter ends with 11534 deals took effective (or completed) by 7880 firms within the sample period.

As with the main measure for market competition, I download the Text-based Network Industry Classification (TNIC) Herfindahl-Hirschman Index from Hoberg and Phillips Data Library[1]. In a recent study, Hoberg and Phillips (2015) develop a new industry classification system based on firm pairwise similarity scores by text analysis on firm's product descriptions from annual firm 10-K filings with the Securities and Exchange Commission (SEC), and it is updated every year. To calculate the Herfindahl-Hirschman Index, it is important to define the "circle" of each firm, or the industry of rivals that each firm compete against. Hoberg and Phillips (2015) create the TNIC industry by web crawling and text parsing algorithms to calculate similarities of firms' business descriptions and define a "circle" of each firm when their business similarities surpassing certain threshold. Their research reveals that firms and industries move considerably within the product space over time, and they view TNIC industries to be far more informative and useful than Fixed Industry Classifications, which include SIC and NAICS. Compared with traditional industry classifications, TNIC is more likely to capture continuous measures of product market similarity and firm relatedness within and across industries. Importantly, the TNIC database is a non-transitive network and every firm has a unique industry. Therefore, the TNIC-HHI calculated is at the firm-year level rather than industry-year level.

B. Descriptive Statistics

Following existing literature on innovation (Fang, Tian, and Tice, 2014; Chemmanur, Loutskina and Tian, 2014, for example), I examine a battery of firm characteristics that may affect the firm's innovation ability. These control variables include R&D intensity, measured by R&D scaled by total assets; capital expenditure intensity, measured by capital expenditure over total assets; firm size, measured by natural logarithm of total assets; profitability, measured by ROA (net income scaled by total assets); asset tangibility, measured by net PPE normalized by total assets; firm

[1] http://cwis.usc.edu/projects/industrydata/industryconcen.htm

leverage, and growth opportunity, measured by market to book value; firm age, which is approximated by the number of years that the firms listed in Compustat. I have also included the institutional ownership, since Aghion, Van Reenen, and Zingales (2013) find that institutional ownership affects innovation output of a firm. Further, to show whether TNIC-HHI is different from the non-linear relation raised by Aghion et al. (2005), I also add in the traditional HHI, which is calculated by the three-digit SIC industry j where firm i belongs, as in recent literature (He and Tian, 2013; Fang, Tian, and Tice, 2014, for example). Detailed variable definitions could be found in Appendix A1.

In reporting the summary statistics of the sample, I winsorize all continuous variables at the top as well as bottom 1% of each variable's distribution, to minimize effects from outliers. Table 1 provides the summary statistics of variables that used in this study, which has a total of 40793 observations.

[*Insert Table 1 Here*]

As we can see from the table, the main concern variable, the TNIC-HHI has the minimum value of 0.01 and the maximum value of 1. Its mean value is at 0.22 while it has the median value of 0.14. On average, the patent number for a given firm that filed in a given year is 6.72 while their total citation for all patent filed in a year for a given firm is around 87.36. Both patent count and citation count are skewed due to the large distance between their mean and median value. Table 1 also reports the descriptive statistics of other control variables. In the sample, an average firm spends 5% and 6% of its assets on R&D and capital expenditures in a year, respectively, and has ROA of 0.07, PPE ratio of 25%, leverage of 20%, market to book value of 2.02, and institutional ownership of 33%. The SIC-based HHI for my sample firm takes the mean value of 0.18. For the suite of new innovation measures, we could see that on average, a firm has 0.35 patents that are new to the firm regarding technology class, 0.12 patents that are highly cited, 0.85 patents that are in the top 10% most cited ranking, 3.08 patents that are moderately cited, 2.68 uncited patents. A firm also has an average of 15.5 self-citations and 101.17 backward-citations in a given year.

C. Pairwise Correlation

In table 2, I report the pairwise correlation matrix among all main variables. As could be seen from the table, both the innovation output measures, patent and citation numbers, which in natural logarithm form, are in negative correlation with the concentration measure, TNIC-HHI (-0.027, for both). The patent number and citation number are highly and positively correlated (0.895). More importantly, I observe that both patent and citation numbers are much more correlated with firm size (0.27 and 0.19), when compared to other variables.

[*Insert Table 2 Here*]

With a glance at other variables, we could find that they are largely consistent with prior literature. Higher M/B, higher ROA, lower leverage, less tangible assets, more R&D spending, older firms, and firms of larger institution holdings have more innovation outputs. Importantly, we could see that the TNIC-HHI is positively related with the traditional HHI, with the correlation of 0.23, which indicates certain differences between the two concentration measures. Also, the TNIC-HHI is negatively correlated with firm size. Above all, whether the negative relation between innovation outputs and TNIC-HHI would be distorted by other firm characteristics is uncertain, we have to turn to multivariate analyses.

V. Empirical Research Results

A. Competition and Innovation Relation

I first investigate the relation between market competition and innovation activities of a firm in the cross-sectional analysis by using the new measure, TNIC-HHI, on competition. Specifically, I run the regression by estimating the following model:

$$Innovation_{i.t,t+2} = \alpha + \beta_1 HHI(TNIC)_{i,t-1} + \delta Z_{i,t-1} + Year_t + Industry_i + u_{i,t} \quad (1)$$

In equation (1), *i* indexes firm, *t* indexes time. Innovation, our dependent variable, can be one of the three measures: Ln(Patent), Ln(Citation), or R&D intensity. For patents and citations, which serve as measures for innovation outputs, will be counted as the number of patents that filed (applied), or total citations received on the firms' patents filed in year t through t+2[2], by following Cornaggia, Mao, Tian, and Wolfe (2015), to reflect the long-term nature of investment in innovation and the cumulative count in innovation could alleviate the idiosyncratic shocks to influence innovation in a certain year. My main variable of market competition is the 10-K Text-based Network Industry HHI (or TNIC-HHI), and I will also add TNIC-HHI-squared to test whether there exists non-linearity.

Besides, Z is a vector of firm characteristics which are commonly used in studying the determinants of innovation, and they are all lagged by one fiscal year in relation to the dependent variable. It consists of firm size, profitability, asset tangibility, leverage, firm age, institutional ownership, capital expenditures, and R&D intensity. Also, if the dependent variable is the R&D intensity, I omit the R&D control in the meanwhile. To show whether TNIC-HHI is different from the non-linear relation raised by Aghion et al. (2005), I also control for the traditional HHI and HHI-Squared term, as in recent literature (He and Tian, 2013; Fang, Tian, and Tice, 2014, for example). Besides, I control for year and industry fixed effects (SIC-2 digit based) to account for variations over time and industries that may influence the innovation activities, and I cluster standard errors at the firm level.

[*Insert Table 3.1 Here*]

In table 3.1, I present the OLS regression results in estimating the equation (1). In columns (1) and (3), I start with a parsimonious model which omits all other control variables except the TNIC-HHI. The regression results indicate a negative relation between TNIC-HHI and innovation, and the estimated coefficients are both significant at 1% level. Moreover, the result in column (5) reveals a negative relation between TNIC-HHI and R&D expenditure and it is also highly significant (at 1% level). To further check whether there is non-linearity, I try to include squared terms of TNIC-HHI, but the coefficients of both TNIC-HHI and TNIC-HHI-Squared turn to be insignificant[3].

[2] The result is robust if the dependent variable is only for year t+2, rather than cumulative sum of innovations for year t through t+2.
[3] Results unreported but available upon request.

In columns (2), (4) and (6) of table 3.1, I estimate the equation discussed above by including all other firm characteristics as well as year and industry fixed effects. I omit variable R&D in fiscal year t-1 when dependent variable is R&D intensity in year t. The estimated coefficients on TNIC-HHI however, turn to reveal an increasing relation between market concentration and innovation output (coefficient estimate of 0.192 for patents, and 0.250 for citations) and decreasing relation between TNIC-HHI and R&D intensity, and all of them are highly significant at 1% level[4]. The evidence suggests that certain variables omitted from the parsimonious regressions could bias the coefficient estimates of *TNIC-HHI* downward.

With an examination of the remaining control variables included in the regression results, we could find they are quite consistent with existing studies on innovation. The regressions show that firms that are larger, and with better growth opportunity, more profitable, lower leverage, higher R&D intensity, higher capital expenditures, and older firms, tend to generate more patents and end with more citations received in future periods. However, I do not find significant relation between institutional ownership and innovation as in Aghion, Van Reenen, and Zingales (2013). Importantly, I find certain evidence of non-linear relation between HHI and innovation, as evidenced by the positive and significant (at 10% level) coefficients of HHI-Squared. I also try to add the TNIC-HHI-Squared term into regression, but it does not show significance in result.

As with R&D spending, the innovation input measure, we could see that firms of smaller size, better growth opportunity firms, less profitable firms, firms of higher capex and higher leverage, and firms with less tangible assets, tend to spend less in R&D. While the coefficient of institutional ownership indicates that higher institutional ownership leads to less R&D expenditure in later periods. I also document an inverted-U relation between the traditional HHI and future R&D spending, but no non-linear relation between TNIC-HHI and R&D expenditure.

Thus far, the regression results indicate a linear cross-sectional relation between firm market power and innovation, which all examined at the firm-year level, and

[4] Results in this part are robust if I restrict my sample to innovative firms (files at least one patent in my sample period) only.

importantly, the new measure on market competition provides some additional explanation power which beyond the traditional market concentration measure in explaining innovation[5].

I next check the within-firm relation between competition and innovation by estimating the model (2). The regression results are is reported in Table 3.2.

$$Innovation_{i,t,t+2} = \alpha + \beta_1 HHI(TNIC)_{i,t-1} + \delta Z_{i,t-1} + Year_t + Firm_i + u_{i,t} \qquad (2)$$

[*Insert Table 3.2 Here*]

Different from Model (1), I add firm fixed effect in regressions by replacing the industry fixed effect, all other control variables remain the same as in model (1). Including the firm fixed effects in my regressions are of two reasons: To be first, it allows us to directly examine if and how the variation in competition power within a firm affects firms' innovation inputs and outputs. Secondly, it helps alleviate the concern that the relationship between TNIC-HHI and innovation could be spurious due to omitted variables (as reflected in the parsimonious model in equation (1)).

The regression results indicate positive and highly significant (all at 1% level) for coefficients of the TNIC-HHI in equation (2), both for parsimonious model and for regressions with other control variables. However, the relation between TNIC-HHI and R&D lose its significance in analysis, indicating that R&D spending does not related much to the change in firm's TNIC-HHI. Finally, I find no significant non-linear relation between the traditional way calculated-HHI and patenting activities[6].

As such, the empirical results above shed light on the relation between market competition and innovation: that there is a positive relation between market competency and innovation outputs and no significant relation between market competency and innovation inputs. This means that for firms with high TNIC-HHI, they generate more patents and receive more future citations, but they do not significantly spend more in R&D.

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[5] Results in this part are robust if I restrict my sample to innovative firms (files at least one patent in my sample period) only.

[6] As argued in Sevilir and Tian (2014), the firm's yearly M&A volume could also affect the innovation outcomes, I add the factor into the regression but turns out not significant (results not reported but available upon request).

B. Exploitative or Explorative

It is interesting to find a dividing relation between the innovation input and output with competition. This raises the question whether high TNIC-HHI firms work more efficiently, or they just exploit their known knowledge at the expense of explorative innovation.

To disentangle the two search trajectory of innovation for firms with different market power, I run a regression of model (2), by replacing the dependent variable to a suite of nuanced innovation measures that aforementioned. I report the regression results in Table 4.

[*Insert Table 4 Here*]

In the first two columns of table 4, I first check the relation between TNIC-HHI and number of citations made to other patents. The larger the number of backward citations, the larger number of prior patents that must be specified in the patent application. Therefore, the measure should correlate with the firm's search intensity in existing know-how and especially, well-known technologies. The other dimension is self-citations, which measures the number of times that a firm cites other patents owned by itself during the patent application. In this way, this measure reflects the degree of search intensity within the firm's boundary. Less self-citations indicate a broader sight of research which goes beyond the firm's technology territory. As could be seen from the results, both the coefficient estimates of TNIC-HHI are positive and significant at 1% level when dependent variables are "Backward citations" and "Self-citations" respectively. Therefore, the evidence is consistent with the first hypothesis that high TNIC-HHI firms tend to pursue their new innovation through exploiting the exiting and well-known technological classes.

Next, I check the number of patents that are filed in technology class that are new or unknown to the company. The dependent variables now change to "Known Classes Patents" and "New classes Patents". Unknown classes are for the technological classes of patents that a given firm has not been granted dating back to the start of the patent database, or 1976. As can be seen from the result, the coefficient for TNIC-HHI in “known classes patents” model are 0.08, significant at 1% level, while the TNIC-HHI coefficient for unknown classes are only 0.029 and moderately significant at 10% level. The results show that the larger patent numbers for high TNIC-HHI firms, when compared with low TNIC-HHI firms, could mainly from the known classes patents. That is, high TNIC-HHI firms prefer to file patents in technology classes that they are familiar with.

Finally, I follow Balsmeier, Fleming, and Manso (2017) to examine the distribution of citations for all the patents in the sample. To be more specific, I check the number of breakthrough (most cited), important (top 10%-2% cited), incremental (cited at least once but not in the top 10% most cited centile), and failed patents for firms with different market power. The regression results, which control for a battery of firm characteristics similar to table 3.2 as well as time and firm fixed effects, are shown in the last four columns of table 4. The results show stark differences for the four types of patents in relation with TNIC-HHI. The coefficient for TNIC-HHI in “TOP 1%”, or number of patents that the firm receives cites within the highest percentile among all the patents in the same three-digit patent class and application year, is 0.019 and significant at 5% level. Similar result is for estimated coefficient of TNIC-HHI for “Top 10%-20%” patents, 0.047 and significant at 5% level. However, there’s a positive and significant (at 1% level) relation between TNIC-HHI and “Cited patents” and the magnitude of the coefficient are two to six times of the “TOP 1%” and “Top 10%-2%”. Finally, I find no relation between TNIC-HHI and the total number of zero-cited patents of the firm. The evidence show that the larger number of patents by high TNIC-HHI firm are mainly moderately cited patents with limited value, rather than highly successful or completely failed patents.

Taken together, results by these nuanced innovation measures are all consistent with my first hypothesis, that while larger TNIC-HHI firms could generate more patents in absolute number, it does not mean they are in a stronger position regarding patent value. But rather, it reveals their innovative strategy is more exploitative than explorative, which could need less in R&D investment.

C. Explanations from M&A

To explore whether M&A are in play for the above relations examined, I first break the full sample into acquirer sample (firms who made at least one acquisition throughout sample period) and non-acquirer sample (firms who never made acquisitions) and I re-run the regressions as in equation (1), the results are reported in table 5.

[*Insert Table 5 Here*]

From the results, we can see that the bidders sample and non-bidders sample yield different relations between TNIC-HHI and innovation: The former discovered TNIC-HHI-innovation relation seems mostly concentrated in the bidders subsample. The estimated coefficients of TNIC-HHI for bidder sample are largely consistent with table 3.1. However, we only find a marginal relation between TNIC-HHI and patent counts and no significant relation between TNIC-HHI and citations. The TNICHHI-R&D relations are quite similar across the two subsamples. This preliminary results show that the relation between TNIC-HHI and innovation could be mainly driven by acquirers. Next, we investigate in detail the M&A in affecting the relationship between TNIC-HHI and innovation.

Further, to examine the impact of M&A on innovation and whether it is competition environment depended, I divide my concentration measure, TNIC-HHI, into high or low concentration group by checking whether the TNIC-HHI of firm i in year t are above or below the sample median. I then check their innovation output before and after M&A for my full sample and each sub-group with high or low market competition. In this way, we could see whether the impact of M&A on innovation for each sub-group (high or low market competition) is even or not. To avoid overlap, I keep the year of the first effective M&A deal as the firm's event year. The sample contains 3634 M&A deals by 3634 firms (one firm at most one deal announced).

Specifically, I run the OLS regression as follows:

$$\mathrm{Ln}(Patent)_{i,t} = \alpha + \beta_1 After_{i,t} + \beta_2 After_{i,t} * Lowmarket_{i,t} + \delta Z_{i,t} + Year_t + Firm_i + u_{i,t} \qquad (3)$$

In equation (3), *i* indexes firms, *t* indexes time. Following Bena and Li (2014), we first use the patent measure in year t, rather than citation, as dependent variable since the point in time at which we count patents is when the patent application is filed with the patent office, and in time it is closest to when the innovation was actually happened. On the other hand, a patent could only be cited when it is rewarded and revealed to the public and an applied patent normally needs an average of 2 to 3 years to get awarded by USPTO, if successful. As such, patent application number in year t could be more exactly to capture the innovation ability of a certain firm in year t than citations. The indicator "*After*", takes the value of one if the firm-year record is one to three fiscal years after the effectiveness of acquisitions, and zero for one to three fiscal years before the effectiveness of acquisitions. The dummy variable "*Lowmarket*", which equals to one if the firm belongs to the low market concentration group, and zero when its TNIC-HHI is below the whole sample median one fiscal year before the deal's effective year[7]. Therefore, in this model set-up, we will not only see whether M&A indeed spurs or impedes innovation, but also we will know whether the impact is the same or not for firms with different pre-merger market competency.

For other control variables, Z is a vector of firm characteristics which are similar to those explained in equation (1). I control for year fixed effects to account for variations over time that may influence the innovation output and time-invariant differences among deals, and I also control firm fixed effect. Finally, I cluster standard errors at the firm level.

[*Insert Table 6.1 Here*]

In column (1) of table 6.1, I show the panel regression result for the whole sample. Our main variable of interest, is the indicator "After". Interestingly, we could see from the results that firms generally suffer a drop (4.8%) in innovation output after completion of M&A. This is manifested by the negative and significant coefficient (at 10% level) of "After". In the second column, I add all control variables in the

[7] Our results do not change if the Low or High market is measured rightly at the effective year.

multivariate regression, the dummy variable remains negative and it is highly significant at 1% level, and ends with larger magnitude (-0.077). Since the dependent variable is in logarithm form, the coefficient of "After" means that firms slow their patenting activities by around 7.7% in the post-merger periods.

In the third column, I go further and check whether the decline takes the same magnitude for firms with different market competency by interacting "After" with the dummy variable "*Lowmarket*". Interestingly, I find that the interaction term is negative and statistically reliable at 1% level. However, the coefficient of "After" is insignificant in result. Combining with the effects shown in the first two columns, this means that the post-merger decline in innovation is mainly driven by firms of low TNIC-HHI pre-merger, while the effect is not prominent if the firms are from high TNIC-HHI group[8].

[*Insert Table 6.2 Here*]

In table 6.2 I also report the regression results from estimating Equation (3) with the dependent variable replaced by Ln(Citation), i.e, the innovation quality rather than quantity. I observe a very similar pattern for the coefficient estimates of *TNIC-HHI* as we add more controls gradually. I observe a negative and significant coefficient estimate of TNIC-HHI in the parsimonious regression without any firm characteristic controls. The coefficient shows that total citations received by acquirers decline by 14.6% in the post-merger period when compared by pre-merger period. The coefficient is resilient if we introduce time-varying firm-specific innovation determinants in the second column of table 6.2. In the third column of table 5, it is much similar with that in the patent analysis: while the patent quality declines by around 12.5% for the high market group, the magnitude is exacerbated for acquirers from low market, which is evidenced by the negative and significant (5%) coefficient estimate of the interaction term "*After*Lowmarket*". This indicates that firm's innovation quality generally declines after takeovers, and it is especially prominent for firms with low pre-merger competency.

In sum, what I find in this part is congruent with my third hypothesis that M&A

[8] All results in this part are robust if I restrict my sample to innovative firms (files at least one patent in my sample period) only.

could weigh on the innovation output, for both quantity and quality for acquirers, at least in a short period after mergers. More importantly, I find that firms of higher market competency do not suffer significant change in patents during the post-merger period, while it is more pronounced in low market concentration group. This means that after major takeovers, the patenting activities are largely dragged down for less powerful firms in the market. These pieces of evidence could lend support to the positive relation between concentration and innovation I discovered in some way: that why less newly applied patents and citations with firms of low market power. The reason could be that, their patenting activities would be greatly disrupted by their takeover activities, resulting in a relatively less newly patents applied when compared to firms of high market competency.

Moreover, as aforementioned, Seru (2014) documents the evidence that firms that are acquired (or targets) in diversifying mergers produce less innovation in the post-deal periods. He also argues that this drop is driven by diversifying mergers with targets involved in non-conglomerating mergers not exhibiting any change in their R&D output. Different from Seru (2014), this study renders a solid evidence on effect of M&A on innovation from the acquirer's side, that the innovation of acquirers could also suffer drop after mergers. What is more importantly, I find that and the decline is mostly severe in firms with less pre-merger market competency. The rationale could be of several folds for these firms, for instance, after major takeovers, they were busy combining the acquired assets into their own assets to ward off the fierce competition in the post-merger periods. Therefore, the post-merger innovative activities will not be of priority and thus, their decline in newly applied patent will be steeper than firms which are well-rooted in the product market. On the other hand, it could also be likely that there is change in the human resources around mergers: that firms with low market power experience innovative scientists exodus after mergers, which could make their innovation activities stagnated.

D. The Quasi-Experiment

In last section, I have found the evidence that M&A could affect the innovation output for firms of different market competency unevenly: with firms of low TNIC-HHI suffer significant decline after M&A while the remaining firms are moderate in scale. However, there still exists endogeneity concern that the impact on patent output could be attributed to other factors or variables that are omitted from our model. To address such concern, I exploit a quasi-experiment to reassure my findings. I follow Seru (2014) and Bena and Li (2014), to employ a control sample of withdrawn transactions which failed for reasons that are exogeneous to innovations.

To be more specific, I include both control deals and treatment deals in my sample. To form my control group, I include a sample of deals with bidders and targets from U.S and were announced between 1996.1.1 and 2003.12.31[9] with the final status flagged as "withdrawn" in SDC. Similar to the M&A filter I imposed in last section, I restrict the transaction volume larger than 1 million; and form of the deal is dubbed as "Merger", "Acquisition of Assets", or "Acquisition of Major Interest" in SDC, and I further drop deals where bidders are from financial industries. Following Seru (2014) and Bena and Li (2014), I keep the deals attitudes of "Friendly" only[10]. Finally, I require that financial information of these firms is available in Compustat/CRSP. For company with multiple failed transactions, I keep the firm's first withdrawn bid in my sample period. In this way, I end with 270 failed deals, and the original sample size of the failed deals is much comparable to that of Sevilir and Tian (2012), Seru (2014) and Bena and Li (2014). Then I read news articles retrieved from Factiva and Google News Search to identify each deal's reasons of the break-up. Following Seru (2014) and Bena and Li (2014), I only keep failed transactions with: 1) objections by regulatory bodies, or 2) unexpected legal action or adverse market conditions, or 3) competing bidders and lose from the biddings. Table 7 gives a description about how I reach a sample of 89 failed biddings that are exogeneous to R&D reasons of bidders or targets.

[*Insert Table 7 Here*]

Next, I form a treatment sample of friendly completed deals over the period 1996

9 Following Bena and Li (2014), I end the sample three years before 2006 to mitigate the potential truncation bias in my post-merger innovation output measure.

10 As argued in Seru (2014), we focus only on friendly deals since unlike hostile takeovers, targets in friendly deals are less likely to change their R&D policies in any irreversible way in order to block the merger.

to 2003 that, 1): occur in the acquirer industry that match the industry (by 2-digit SIC) of the bids in control sample, and 2): announced within three-year window centered at the announcement year of the bids from the control sample. Then, I select, at most, 3 closest completed deal (i.e, 1 control bids for, at most, 3 treatment bids) in terms of the relative size ratio (computed by deal value scaled by firm asset) from the industry and event window-matched deals. I drop control deals without matched treatment deals in 1) and 2). Using this approach, I ensure that my treatment and control deals are similar in both industry composition and time clustering (Roberts and Whited, 2011).

Further, to avoid overlap, for a given bidder in a given year, if there are multiple deals announced by the bidder and there are multiple deal outcomes (failed and successful), I drop the firm-year observation. My final sample consists of 27 controlled deals with 52 treatment deals matched[11]. Among them, 14 control bids and 23 matched-treatment bids are acquirers from the "Lowmarket" group one fiscal year before the effective/withdrawn year, while 13 control bids and 29 matched-treatment bids are acquirers from the "Highmarket" group one fiscal year before the effective/withdrawn year.

I then use a similar regression as in Bena and Li (2014) to estimate the treatment effect,

$$Ln(Patent)_{i,t} = \alpha + \beta_1 After_{i,t} + \beta_2 After_{i,t} * Treatment_{i,t} + Deal\ FE_i + Year\ FE_t + u_{i,t} \quad (4)$$

In the above equation, "*After*" equals one for the post-merger (successful or withdrawn) period (cyr+1 to cyr+3), and zero for one to three years before the announcement of the deal (ayr-3, ayr-1). "*Treatment*" equals one for treatment group (successful bids) and zero for control group (failed mergers). Following Bena and Li (2014), I include deal fixed effect to rule out any time-invariant differences among

[11] For the control deals, some could only matched less than 5 treatment deals (but at least one matched successful deal). The control group sample size is comparable to Bena and Li (2014).

different transactions. I also include year fixed effect to difference away the common trend that may affect deals from both treatment and control groups. This could help see whether acquisitions hurt innovation of firms with low TNIC-HHI the most or not and whether the difference is due to the treatment effect or not.

[*Insert Table 8 Here*]

In Panel A of table 8, I report the regression results of equation (4) by first break my sample into low and high market competition subsample that stated above. From the first column, the coefficient estimate for "*After*" is negative and significant at 1% level for low market failed bidders, suggesting that the low market acquirer's innovation output is, on average, smaller in the post-merger period. Also, the interaction term "*After*Treatment*" is positive and highly significant at 1% level. This coefficient indicates that succeed in completing an M&A deal could lead to a less steep drop in the innovation output for acquirers with low market power. In the second column however, I find that for firms with high market power in our sample, are of no significant change regarding the innovation output in the post-merger period, as indicated by the insignificant coefficient of "*After*". More importantly, I show that the coefficient of the interaction term "*After*Treatment"* is also not significant either. The evidence above suggests that the pre-merger market concentration is a crucial determinant of the effect of an acquisition on post-merger innovation output. Importantly, it reveals that the takeovers could only take material effect on firms with low market power regarding innovation activities.

Next, I use my panel data to run the equation as below by including all the samples to directly check the heterogeneity in the treatment effect of a merger on post-merger innovation output:

$$Ln(Patent)_{i,t} = \alpha + \beta_1 After_{i,t} + \beta_2 After_{i,t} * Treatent_{i,t} + \beta_3 After_{i,t} * Lowmarket_{i,t} + \\ + \beta_4 After_{i,t} * Lowmarket_{i,t} * Treatent_{i,t} + Deal\ FE_i + Year\ FE_t + u_{i,t} \quad (5)$$

In equation (5), as before, dummy variable "*Lowmarket*" equals to one if the firm-year is below the sample median, and zero otherwise one fiscal year before the deal's effective/withdrawn year. As in Bena and Li (2014), we cannot estimate the coefficients on $Treatent_{i,t}$ or $Lowmarket_{i,t} * Treatent_{i,t}$, since both terms are subsumed by deal fixed effects that we imposed. Column 3 of Panel A in table 8 reports the regression result of equation (5). I find that coefficient of the interaction term "*After*Lowmarket*" is negative and significant at 1% level, indicating a significant drop by control group of "Lowmarket" firms. Importantly, the coefficient of "*After*Lowmarket*Treatment*" is positive and significant at 10% level. This result again proves that M&A could significantly affect the patent output for firms of low market concentration: after takeovers, the drop in patenting activities of failed bidders with low market concentration is much steeper than their successful counterparts.

The validity of a Difference-in-Differences test relies on the satisfaction of the key identification assumption, the "parallel trend" assumption, which states that without the treatment effect, the observed Dif-in-Difs estimator will be zero. Therefore, I follow Bena and Li (2014) to implement a placebo test whereby I falsely assume the -4 year (real effective year minus by 4) as the pseudo-event year and run the regressions to analyze the innovation change of treatment and control bidders during the 7-year window surrounding the pseudo-event year. Table 8 Panel B reports the placebo test results. As can be seen, none of the coefficient estimates of "After*Treatment" in column (1) and (2) as well as the coefficient estimate of "After*Lowmarket*Treatment" in full sample are statistically significant, showing that the parallel trend assumption to hold in my sample construction.

In sum, this quasi-experiment above verifies that M&A could, at least partially, affect firm's innovative incentives in a short period: firms of low pre-merger market competency suffer pronounced decline in innovation after mergers while firms of high market power are relatively immune from the disruption of M&A. This kind of "immunity" from takeovers explains, or at least in part, why high market group yields a relatively larger patent output when compared with the remaining firms.

D. Exploring the Underling Channel: Evidence from the inventor-level

In this part, I try to dig out the reason, or underling mechanism, that drives the post-merger behavior differences between low and high market competency firms.

Following Bernstein (2015) and Seru (2014), I examine the issue from the inventor level. Analysis from the inventor-level is quite challenging in literature of innovation. Though the patent database provides both the name of the inventor and its assignee for each patent, it is generally not readily available for analysis due to several reasons: First, the inventors' names recorded in the database are not reliable as their first names are often be abbreviated and different inventors could result in similar or identical names. Second, as argued in Bernstein (2015), that though it is possible to infer the mobility of an inventor across different employers which due to the employers' corporate activities (IPO, M&A, etc.), it is difficult to know the precise date of the relocation, and transitions for those inventors who do not file patents in the new employers are not observable.

Therefore, I use the Harvard Business School (HBS) patent database, which provides each inventor a unique identifier for patents filed from year 1975 through 2010. The HBS project (see Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming, 2014, for detailed description [12]) uses a Bayesian supervised learning approach and disambiguation algorithms to separate inventors based on a series of characteristics (First, middle and last name, geographical location, patent technological class, assignee, etc.) and generate each scientist a unique number. I attribute a patent equally to each inventor when a patent filed include multiple inventors. I create a balanced data set by collapsing the information to one observation before and one after, for all the successful M&A events in the paper's second section. In other words, each inventor for each assignees appears in pair before and after the event. In the end, my sample has information about 1191 M&A deals by 1191 innovative firms with 130000 patents and 71219 unique inventors involved (1.8 patents per scientist on average). Also, note that certain inventors could appear simultaneously in multi-events for different firms, and one inventor could file patents for multi-firm in the same year through co-authorship (collaborating with inventors from another company) on

[12] I would like to thank Li, et al. working on the project for providing data for public access.

certain patents.

Follow Seru (2014), I construct a dummy variable, *"Present"*, which takes two values for each inventor: a value one (zero) before the event if the inventor is present (not-present) in five years before the event and a value of one (zero) after the event if the inventor is present (not present but files at least a patent in another company[13]) in five years after the event. Also, following Bernstein (2015), I define "Stayers" as inventors that present (file at least a patent) at the same firm both before and after the event and "Leavers" as inventors that present at the firm (file at least one patent) before the event and do not present at the firm (and file at least one patent in a different firm) after the event. There are, two margins which could be explain the decline in R&D productivity around the merger event: one is the "extensive margin", whereby more creative inventors may leave the bidders after mergers; and on the "intensive margin", whereby individuals may choose to stay in the firm but become less productive on innovative activities. Due to the co-authorship, one inventor could file patents for more than one company in the same year and it is hard to find out who's exactly the inventor's employer. In this circumstance, I attribute this inventor equally to these assignees.

I run a panel regression as follows (model 6). The dummy variable "After" takes the value of one if the inventor-year record is after the completion/withdraw year of acquisition(s), and zero if the inventor-year before the completion/withdraw year of acquisition(s). "Lowmarket" takes the value of one if the employer's TNIC3-HHI is below the sample median one fiscal year prior to the completion of M&A and zero otherwise. I control a battery of firm characteristics before and after mergers, similar as in equation (3). Finally, I impose inventor as well as year fixed effect in the same time for the Logit regression model at the inventor-level. The regression result of model (6) is reported in table 9:

$$Logit(Present = 1)_{i,t} = \alpha + \beta_1 After_{i,t} + \beta_2 After_{i,t} * Lowmarket_{i,t} + Year\ FE_t\ +$$

[13] This is to ensure all inventors in my sample are "Active" inventors, which means their disappearance from the post-event periods is not due to reasons like death, occupation change, etc.

$$Inventor\ FE_i + Control\ Variables_{i,t} + u_{i,t} \quad (6)$$

[*Insert Table 9 Here*]

In Column 1 of Panel A in table 9, the "extensive margin", I first check the mobility change for all the inventors in our sample. The result clearly shows that the coefficient estimates for "After", or β_1, is positive and significant at 5% level, indicating that more inventors seem to be in the original assignees after the takeovers (likelihood by 7.6%)[14]. In Column 2 of table 9, I add an interaction term to separate the inventors from Low market competency firm and High market competency firms. I find that while β_1 is still positive and significant at 1% level, and β_2 is negative and significant at 1% level, showing that in the post-merger periods, firms from high market group have higher likelihood to retain their inventors after mergers (by 12%), while low market group has high likelihood to suffer inventor exodus after mergers ($\beta_1 + \beta_2$ is negative). The overall result is interesting since it reveals that while some newcomers will join the high market acquirers to make their R&D team stronger after the mergers generally, some firms may also experience innovator exodus, which hinders their innovation activities.

Following Seru (2014), I next check the change at intensive margin, that is, I examine the productivity change by stayers surrounding the event. In column (3) to (6) of Panel A in table 9, Ln(Stayer Patents) (or Ln(Stayer Citations)) is the natural logarithm of patents (or total citations received by patents) filed by inventors that remain inside the firm after the event, and it takes two values for each inventor: the natural logarithm number of patents (or citations) within 5 years before the event and the natural logarithm of total patents (or citations) within 5years after the event. I keep the latest patents by inventors that filed in five years surrounding the event year to examine the stayers' latest productivity. The results show that, after the event, the innovation quantity for stayers get enhanced for retained inventors in the high market firms, but there's decline in patent counts for inventors from the "Lowmarket" firms.

[14] The observation in logit regression drops from the original 87794 to 30192 due to the fixed effect imposed.

Also, inventors from both the low and high market firm suffer decline in innovation quality after mergers, and the decline is more severe for stayers from the low market group. This also explains well why the post-merger innovation quality is lower for high market firms either, as shown in table 6.

Next, I compare the pre-merger productivity between stayers and leavers for different pre-merger market competency and the result is presented in Panel B of table 9. It could be clearly seen from the results that, leavers from the high market are less productive than stayers in pre-merger period in both innovation quality and quantity, and the differences are similar for inventors from the low market firms. The results show that less productive inventors are less likely to be retained in the original company surrounding mergers, irrespective of their employers' pre-merger market competency. In panel C of table 9, I show that newcomers who join the Low market competency firms are more productive than newcomers who join the high market competency firms (4.2% more patents and 24.7% more citations received).

What's the productivity change for leavers who join a new company, before and after the inventor's reallocation? I answer the question in Panel D of table 9 by pairing the firm characteristics of the original and new employers. The dummy variable "*Exit from Lowmarket*" is equal to one if the original employer of the inventor is of low market competency before its mergers and zero otherwise. In the similar way, dummy variable "*Join Lowmarket*" is equal to one if the new employer of the inventor is a low market firm during the year when the new comer first file a patent, and zero otherwise. Column 1 and 2 of panel D show that leavers' productivity increased after mergers (by around 20% of more patents), but it does not related with who the original employers are, as evidenced by the interaction term "*After*Exit from Lowmarket*". However, in the third column of Panel D, when we further split the new employer's market condition, it shows that inventors who left from a "low market" firm and later joined a "high market" firm has their patents increased in the post-merger period, while inventors who later join a "low market" firm ends with less patents in result. Therefore, the "low out, high in" inventors seems to excel "low out, low in" inventors in productivity change. Similar evidence is found regarding the innovation quality regarding leavers surrounding, except that the quality in the post-merger periods generally declines for leavers when joining a new company.

To put together the evidence from the “extensive margin” and “intensive margin”, analyses in this part lays bare one of the reasons why firms of low market competency suffer severe drop in innovation in the post-merger periods, that is, they seem to suffer scientist exodus after mergers, which in result stagnating the innovative activities of acquirers, and the stayed individuals produce less impactful patents after mergers. But for high market companies, their R&D team gets stronger and their incumbent inventors’ productivity get enhanced after mergers, which will keep the firm’s overall innovation activities resilient surrounding mergers. Further, high market companies could attract inventors who have their innovative potential released after these scientists joining the company.

E. The Pairing Issue: Who-acquires-whom?

Next, I explore the M&A pairing issue in our setting. As I discussed in the hypotheses above, firms with low market power could spend high in R&D and make themselves ideal targets for later acquisitions. I am curious to know the pairing issues of M&A regarding firms of different market power. That is, which kinds of firms are more likely to become acquirers while others be the targets regarding different market powers? In the sample, I involve all successful announced biddings and I am successfully to locate the market information of 1379 public targets with basic firm information as well as their TNIC-HHI info.

To verify the hypothesis, I run a *Probit* regression for the equation below:

$$Probit(To\ be\ Acquirer/\ To\ be\ Targeted)_{i,t} = \alpha + \beta_1 HHI(TNIC)_{i,t-1} + Z_{i,t-1} + Year\ FE_t + Industry\ FE_t + u_{i,t} \quad (7)$$

In equation (7), the dependent variable is dummy variable *“To be Acquirer”* or *“To be Targeted”. “To be Acquirer”* is equal to one if the firm announces a takeover in the next fiscal year and zero otherwise. The dummy variable *“To be Targeted”* is set to one if the firm becomes a target in one fiscal year following the firm-year record and zero otherwise. I use all the M&A deal in our sample to identify the two dummies. When one firm announces multi deals, I only count it once in the firm-year record. I have also control other firm characteristics as well as year and industry fixed effect, and I cluster standard errors at firm level.

[*Insert Table 10 Here*]

In Table 10 I report the *Probit* regression for equation (7). As could be seen from the first column, there is no significant relation between TNIC-HHI and the probability of a firm to become an acquirer, as evidenced by the insignificant estimate of β_1 in equation 7[15]. In other words, firms from low or high market are of equally likelihood to takeover other firms, even control for relating factors. Since we find some pieces of evidence that low market firms suffer steeper drop in innovation in post-merger periods, which explains the relatively less patenting activities of them when compared to high market firms. The regression in equation 7 could help dispel the concern that though the disruption of takeovers in innovation is more severe among low market power group, it is likely that low market group has less deals announced when compared with high market group.

For remaining control variables in table 10, we could find that larger firms, firms with better growth opportunity, profitability, larger institutional ownership, less tangible assets, R&D spending, and older firms, are more likely to become acquirers.

In the second column of table 10, I examine which type of firm are more likely to become targets. We could find that when TNIC-HHI goes larger, there is a smaller likelihood to become later targets, since the estimate of β_1 is negative and highly significant in 1% level. In other words, firms of low market competency are more likely to be acquired in later periods. As with other control variables, we could find that firms of smaller size, lower growth opportunity, lower profitability, higher leverage, less tangible assets and higher R&D and Capex spending, are more likely to be targeted in later period.

[15] I have also tried to add squared term of TNIC-HHI, but the coefficient estimates are not significant.

As such, our findings indicate that firms from the lowest concentration quintile, are more likely to be acquired in later years. The characteristics of high R&D and high patenting could indicate that these firms spend high in R&D not only for survival in the market, but also for the expectations that they will become targets in later period. This finding also echoes Bena and Li (2005) and Phillips and Zhdanov (2013) that firms of low innovation output high R&D spending are usually targets and to be acquired is one of their exit choices.

If firms in the lowest concentration quintile are most likely to become targets, so a natural question is where are the acquirers from?

I test an empirical model as below:

$$Probit(Target\ from\ Q(m))_{i,t} = \alpha + \beta_1 Acquier\ from\ Q(i) Mareket_{i,t-1} + Z_{i,t-1} + Year\ FE_t + Industry\ FE_i + u_{i,t} \qquad (8)$$

In model 8, the dependent variable is equal to one if the target's firm-year is from the m's quintile of the TNIC spectrum (sorted by all the firms in year t) and zero otherwise. I add four depend variables *Acquirer from Q(i)Market* to indicate which quintile the related acquirer comes from. I cut my sample into 5 quintiles according to their TNIC-HHI sorting in each year, I then put 4 of them as dummy variables each time for the regression and the results are shown in Table 11.

[*Insert Table 11 Here*]

As could be seen from the first column of Table 11, the coefficient of Acq_Q1market is significant and largest among the four quintile indicators. This evidence suggests that when compared to firms from Q2-Q4 quintile, firms of the lowest market TNIC-HHI distribution are most likely to become acquirers for targets from smallest TNIC-HHI quintile. Similar pattern shows in column (2) and (3), whereby targets and acquirers from similar TNIC-HHI sorted quintiles are most likely to be paired in mergers. In columns (5), I change the dependent variable to "*Target from Q(5)",* which is equal to one if the target is from the highest quintile of market concentration and zero otherwise. As could be seen from the coefficients, the first to third quintile acquirers are least likely to acquire the high market concentration targets, as evidenced by the negative and significant coefficients of the related dummy variables, while the Q4 is not significant. In other words, the acquirers from more large market power group are more likely to acquire targets from the higher TNIC-HHI group. In all, the results reveal a "like-buys-like" pattern that most likely, the firms reside within the lowest or highest market concentration groups are actually takeover each other, and rarely "invade" other market concentration regimes. Importantly, this evidence contradicts with my second hypothesis that firms with large patent outputs but less R&D inputs, who have larger TNIC-HHI, tend to acquire firms with less patent outputs but more intensive R&D spending, who have smaller TNIC-HHI.

VI. Conclusion

In this paper, I revisit the relation between market competition and corporate innovation by using a new market structure measure. Different from more recent literature like Aghion et al. (2005), I document a linear relation between newly applied patents, their future citations, R&D spending, and market competencies. The market concentration index, is a novel text-based measure borrowed from Hoberg and Phillips (2015), which enables me to investigate the relation in a firm-level rather than prior studies of industry-level. While the core intention in this study is not to join the debate of the relation itself, I try to find new explanations that could shape the relation. Importantly, I provide new explanations of the linear relation by using a suite of nuanced innovation measures and the theory borrowed from corporate takeovers.

The study finds that that firms with higher market power file more patents and receive more future citations, but they do not spend significantly more on R&D. The innovative strategies for firms of higher market competency are more exploitative than explorative, and they focus on more familiar and crowed areas of technology, which need less R&D input. The citations received by high TNIC-HHI firms, mainly come from patents that in the middle of the citation distribution, rather than uncited and highly cited innovations.

This study also raises the notion of "acquisition hurts innovation" in some way. I find that firms generally experience decline in newly applied patents in their post-merger period, but the decline is mostly by firms of low market competency, while firms of high market competency do not seem to significantly suffer this innovation decrement after M&A. This finding accords well with my discoveries on why firms of high market power have more innovation output when compared with the remaining companies across industries. I design a quasi-experiment by using failed bids to confirm my findings. Besides, I also find that firms which belong to the smallest market power group are more likely to be acquired in later years, which means that they spend intensively in R&D, not only for the sake of market survival, but also for attracting future takeovers. These firms of relatively low or high market power generally acquire each other in the takeover market, which is another dimension of acquisition pairing issue in M&A. My study also goes into the inventor-level at the buyer's side in M&A, to provide an underling channel for the differences in post-merger patenting activities for firms of different market competiveness. I find that firms of low market competency experience higher likelihood of inventor exodus after mergers than firms of high market power, and their retained innovators exhibit smaller improvement in quantity of innovation after mergers. Moreover, inventors left from a low market competency firm and joined a high market competency firm get their innovative ability enhanced after mergers, which help high market firm's innovative activities keep resilient after mergers. The inventor-level evidence provides unique insights into the change in innovation surrounding corporate takeovers. Further study could drill deeper into characteristics of firms with either low market competency or high market competency, and explore other reasons in explaining their divergent patenting habits.

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Appendix

Table A1 Variable Definitions

This table presents the definitions of variables used in our sample. Firm-related data is from the Compustat from year 1996-2006. Patent data is from the NBER patent database from year 1996-2006. M&As deal-related data is from the Securities Data Company (SDC) from year 1996-2006. Inventor-level data is from HBS patenting database from year 1975-2010. Market concentration data is from Hoberg and Phillips (2014) from 1996-2006. All continuous variables are winsorized at the 1% and 99% levels.

Variable	Definitions
Firm-level variables	
After (0/1)	Dummy variable: takes the value of one if the firm-year record is one to three fiscal years after the completion of acquisition(s) and zero for one to three fiscal years before the acquisitions.
Firm Size	Natural logarithm of book value of assets.
M/B	Market value of assets over book value of assets.
Leverage	Total debt normalized by total assets.
ROA	Operating income before depreciation normalized by total assets.
Capex	Capital expenditures normalized by total assets.
R&D	R&D expenditures normalized by total assets. We set this value to zero if R&D is missing.
PPE	Net property, plant, and equipment normalized by total assets.
Inst.Ownership	Total percentage of firm’s equity held by institutional investors.
Firm Age	Natural logarithm of firm’s age, which is approximated by the number of years listed on Compustat.
Measures of Innovation Activities	
Ln(Patent)	Natural logarithm of one plus firm i's total number of patents filed (and eventually granted) in year t.
Ln(Citation)	Natural logarithm of one plus firm i's total number of citations received on the firms’ patents filed (and eventually granted) in year t.
Ln(Top 1%)	Natural logarithm of one plus firm i’s total number of patents that fall into the 1% most cited patents within a given three-digit technology class and application year.

Ln(Top 10%-2%)	Natural logarithm of one plus firm i's total number of patents that fall into the 10-2% most cited patents within a given three-digit class and application year.
Ln(Cited Patents)	Natural logarithm of one plus firm i's total number of patents that received at least one citation but do not appear in the top 10% of the citation distribution.
Ln(Uncited Patents)	Natural logarithm of one plus firm i's total number of patents that were not cited.
Ln(Self-citations)	Natural logarithm of one plus firm i's total number of cites to patents held by the same company.
Ln(Back-citations)	Natural logarithm of one plus firm i's total number of cites that made to prior patents.
Ln(New/Known Classes)	Natural logarithm of one plus firm i's total number of patents that are field in classes where the given firm has filed no/at least one other patent beforehand in year t.
Measure of Competition	
TNIC-HHI	Concentration measure from Hoberg and Phillips (2015). The industry classifications are based on firm pairwise similarity scores from text analysis of firm 10K product descriptions. (We downloaded the data from Hoberg-Phillips data Library website: http://alex2.umd.edu/industrydata/industryconcen.htm). A higher TNIC-HHI index indicates a greater concentration in the industry.
HHI	Herfindahl-Hirschman Index, calculated by the 3-digit SIC industry j where firm i belongs, measured at the end of fiscal year t.
Lowmarket (0/1)	Dummy variable, takes the value of one if the firm's TNIC-HHI is below the sample median one fiscal year prior to the M&A and zero otherwise.
Highmarket (0/1)	Dummy variable, takes the value of one if the firm's TNIC-HHI is above the sample median one fiscal year prior to the M&A and zero otherwise.
Inventor-level variables	
Present (0/1)	Dummy variable, takes two values for each inventor: a value one (zero) before the event if the inventor is present (not-present) in any years before the event, and a value of one (zero) after the event if the inventor is present(not present) in any years after the event.
Stayer	The inventor presents (files at least a patent) at the same firm both before and after the merger event.
Leaver	The inventor presents at the firm (files at least one patent) before the event and does not present at the firm (and files at least one patent in a different firm) after the merger event.

Table 1 Summary Statistics

This table reports the summary statistics for variables constructed based on the universe of Compustat firms from 1996 to 2006. The observational unit is firm-year. Information on firm's characteristics is from Compustat. Patents and citations' information is from NBER patent database from 1996 to 2006. Market concentration data, the TNIC-HHI, is from Hoberg-Phillips data Library. All variable definitions are in table A1. All continuous variables are winzorized at 1% and 99% percent.

VARIABLES	N	Mean	Median	SD	Min	Max
Patent	40793	6.72	0.00	70.99	0.00	4,344
Citation	40793	87.36	0.00	1,236.54	0.00	104,907
TNIC-HHI	40793	0.22	0.14	0.22	0.01	1.00
Firm Size	40793	5.45	5.36	1.92	1.64	10.30
M/B	40793	2.02	1.40	1.74	0.58	11.21
Leverage	40793	0.20	0.16	0.18	0.00	0.70
ROA	40793	0.07	0.10	0.17	-0.69	0.39
R&D	40793	0.05	0.00	0.09	0.00	0.48
Firm Age	40793	19.87	16.00	13.91	1.00	83.00
Capex	40793	0.06	0.04	0.06	0.00	0.35
PPE	40793	0.25	0.18	0.23	0.01	0.89
Inst.Ownership	40793	0.33	0.25	0.31	0.00	1.00
HHI	40793	0.18	0.12	0.16	0.01	1.00
New Classes	40793	0.35	0.00	1.51	0.00	74
Known Classes	40793	6.38	0.00	70.37	0.00	4,335
Top 1%	40793	0.12	0.00	1.24	0.00	58
Top 10%-2%	40793	0.85	0.00	8.79	0.00	441
Cited Patents	40793	3.08	0.00	41.70	0.00	3,101
Uncited Patents	40793	2.67	0.00	29.44	0.00	1,845
Self-citations	40793	15.50	0.00	214.21	0.00	14,416
Backward-citations	40793	101.17	0.00	989.62	0.00	53,222

Table 2 Pairwise correlation matrix

This table reports the pairwise correlations across our main variables. Correlations that are significant at 1% level are in bold. All variable definitions are in TableA1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)Ln(Patent)	1.000												
(2)Ln(Citation)	**0.895**	1.000											
(3)TNIC-HHI	**-0.027**	**-0.027**	1.000										
(4)Firm Size	**0.273**	**0.192**	**-0.219**	1.000									
(5)M/B	**0.178**	**0.186**	**-0.028**	**-0.139**	1.000								
(6)ROA	**0.051**	**0.053**	**0.034**	**0.324**	**-0.086**	1.000							
(7)Leverage	**-0.051**	**-0.060**	**0.042**	**0.290**	**-0.274**	**0.136**	1.000						
(8) R&D	**0.213**	**0.203**	**-0.095**	**-0.291**	**0.342**	**-0.523**	**-0.294**	1.000					
(9) Capex	0.008	**0.034**	**-0.037**	-0.006	**0.064**	**0.147**	**0.125**	**-0.064**	1.000				
(10) PPE	**-0.046**	**-0.041**	**-0.044**	**0.189**	**-0.158**	**0.237**	**0.402**	**-0.242**	**0.611**	1.000			
(11)Firm Age	**0.168**	**0.100**	**0.031**	**0.422**	**-0.161**	**0.202**	**0.140**	**-0.167**	**-0.044**	**0.191**	1.000		
(12)Ins.Ownership	**0.214**	**0.156**	**-0.048**	**0.434**	**0.059**	**0.261**	-0.005	**-0.038**	**0.042**	**0.023**	**0.189**	1.000	
(13)HHI	**0.023**	0.009	**0.229**	**0.028**	**-0.071**	**0.128**	**0.093**	**-0.142**	**0.040**	**0.096**	**0.127**	**0.117**	1.000

Table 3.1 Competition and Innovation Relationship: Cross Sectional Analysis

This table reports the cross sectional regression results for the relationship between innovation and competition. The patent and citation measures are aggregated from year t through year t+2. Competition is measured by Text-based Network Industry Classification (TNIC) HHI from Hoberg and Phillips (2015). All control variables are lagged by one fiscal year relative to dependent variables. Other variable definitions are in Table A1. Fixed effects based on year and 2-digit SIC based industries are imposed. Robust standard errors are clustered at the firm level. In parentheses are t-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Ln(Patent)	Ln(Patent)	Ln(Citation)	Ln(Citation)	R&D	R&D
	b/t	b/t	b/t	b/t	b/t	b/t
TNIC-HHI	-0.590***	0.192***	-0.751***	0.250***	-0.071***	-0.060***
	(-9.463)	(3.490)	(-9.636)	(3.608)	(-22.373)	(-21.693)
Firm Size		0.334***		0.401***		-0.003***
		(21.851)		(23.746)		(-6.168)
M/B		0.082***		0.124***		0.006***
		(11.910)		(12.538)		(13.402)
ROA		0.217***		0.483***		-0.204***
		(3.228)		(4.983)		(-33.423)
Leverage		-0.419***		-0.643***		-0.052***
		(-6.140)		(-7.397)		(-16.928)
R&D		2.435***		3.466***		
		(14.283)		(14.417)		
Capex		0.746***		1.120***		0.051***
		(4.586)		(4.870)		(5.365)
PPE		-0.112		-0.087		-0.033***
		(-1.207)		(-0.766)		(-8.401)
Firm Age		0.065***		0.078***		-0.001
		(3.201)		(3.005)		(-1.447)
Ins.Ownership		-0.053		-0.059		0.009***
		(-0.901)		(-0.834)		(4.239)
HHI		-0.143		-0.262		-0.093***
		(-0.492)		(-0.744)		(-7.656)
HHI Squared		0.548*		0.760*		0.090***
		(1.665)		(1.951)		(7.186)
_cons	-0.310***	-2.978***	-0.475***	-3.806***	0.017***	0.057***
	(-14.423)	(-18.748)	(-16.839)	(-20.806)	(13.087)	(12.139)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
N	40793	40793	40793	40793	40793	40793
Adjusted R-Squared	0.199	0.385	0.210	0.349	0.304	0.492

Table 3.2 Competition and Innovation Relationship: Firm Fixed Effect

This table reports the panel regression result for the relationship between innovation and competition in fixed effect model. The patent and citation measures are aggregated from year t through year t+2. Competition is measured by Text-based Network Industry Classification (TNIC) HHI from Hoberg and Phillips (2015). Other variable definitions are in Table A1. Fixed effects based on year and firm are imposed. Robust standard errors are clustered at the firm level. In parentheses are t-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Ln(Patent) b/t	Ln(Patent) b/t	Ln(Citation) b/t	Ln(Citation) b/t	R&D b/t	R&D b/t
TNIC-HHI	0.119***	0.120***	0.294***	0.280***	-0.000	-0.001
	(3.551)	(3.615)	(4.153)	(3.997)	(-0.133)	(-0.767)
Firm Size		0.073***		0.096***		-0.005***
		(4.236)		(2.810)		(-4.407)
M/B		0.051***		0.099***		-0.001***
		(9.976)		(9.890)		(-3.263)
ROA		0.006		0.294**		-0.058***
		(0.094)		(2.495)		(-9.868)
Leverage		-0.323***		-0.555***		-0.021***
		(-5.240)		(-4.515)		(-5.698)
R&D		0.360**		0.934***		
		(2.027)		(2.744)		
Capex		0.072		0.286		0.027***
		(0.689)		(1.300)		(3.908)
PPE		0.211**		0.599***		0.017***
		(2.304)		(3.077)		(3.223)
Firm Age		0.139***		0.428***		-0.001
		(3.883)		(5.530)		(-0.312)
Ins.Ownership		-0.149***		-0.493***		-0.006**
		(-3.094)		(-4.946)		(-2.208)
HHI		-0.128		0.269		-0.004
		(-0.467)		(0.461)		(-0.391)
HHI Squared		0.124		-0.167		0.002
		(0.465)		(-0.286)		(0.203)
_cons	-0.100***	-1.001***	-0.352***	-2.416***	0.045***	0.087***
	(-3.720)	(-6.152)	(-7.915)	(-6.885)	(43.924)	(10.113)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
N	40793	40793	40793	40793	40793	40793
R-Squared	0.839	0.842	0.711	0.717	0.872	0.877

Table 4 Competition, the Distribution of Citations and Type of Patents

This table reports the panel regression result for the relationship between competition, distribution of citations and number of patents in different types in fixed effect model. Backward-citations are total number of cites that made to prior patents. Self-citations are total number of cites to patents held by the same company. Patents in new/known classes is the total number of patents that are field in classes where the given firm has filed no/at least one other patent beforehand in year t. Top 1% are of patents that fall into the 1% most cited patents within a given three-digit class and application year. Top 10%-2% are patents that fall into the 10-2% most cited patents within a given three-digit class and application year. Cited patents are total number of patents that received at least one citation but do not appear in the top 10%. Uncited patents are total number of patents that were not cited. Competition is measured by Text-based Network Industry Classification (TNIC) HHI from Hoberg and Phillips (2015). Other variable definitions are in Table A1. Fixed effects based on year and firm are imposed. Robust standard errors are clustered at the firm level. In parentheses are t-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Ln(Backward-citations) b/t	Ln(Self-citations) b/t	Ln(Known Classes) b/t	Ln(New Classes) b/t	Ln(Top 1%) b/t	Ln(Top 10%-2%) b/t	Ln(Cited Patents) b/t	Ln(Uncited Patents) b/t
TNIC-HHI	0.179***	0.083***	0.080***	0.029*	0.019**	0.047**	0.117***	0.014
	(3.341)	(2.904)	(3.140)	(1.804)	(2.094)	(2.417)	(3.616)	(0.695)
Firm Size	0.160***	0.077***	0.087***	0.034***	0.011***	0.038***	0.053***	0.075***
	(6.334)	(5.684)	(6.600)	(4.389)	(3.098)	(4.496)	(3.620)	(7.209)
M/B	0.076***	0.031***	0.035***	0.022***	0.008***	0.026***	0.036***	0.027***
	(9.390)	(6.839)	(9.188)	(8.227)	(5.950)	(8.748)	(7.776)	(8.621)
ROA	-0.083	-0.058	-0.015	0.079***	-0.011	-0.006	0.219***	-0.145***
	(-0.877)	(-1.249)	(-0.358)	(2.875)	(-0.895)	(-0.210)	(4.810)	(-4.213)
Leverage	-0.436***	-0.194***	-0.228***	-0.064**	-0.012	-0.102***	-0.212***	-0.119***
	(-4.626)	(-3.636)	(-4.775)	(-2.195)	(-0.913)	(-3.219)	(-3.982)	(-2.993)
R&D	0.580**	0.259*	0.379***	0.118	0.030	0.136	0.709***	-0.043

	(2.086)	(1.764)	(2.940)	(1.408)	(0.834)	(1.617)	(5.092)	(-0.399)
Capex	0.176	0.037	0.050	0.134***	0.034	0.033	0.211**	-0.104
	(1.048)	(0.453)	(0.672)	(2.583)	(1.446)	(0.694)	(2.391)	(-1.632)
PPE	0.243*	0.138*	0.171**	0.127***	0.013	0.123**	0.375***	-0.013
	(1.769)	(1.846)	(2.549)	(3.090)	(0.553)	(2.566)	(4.437)	(-0.254)
Firm Age	0.157***	0.240***	0.191***	0.044***	0.036***	0.115***	0.336***	-0.006
	(3.176)	(8.059)	(6.882)	(2.624)	(3.895)	(5.332)	(8.499)	(-0.332)
Ins.Ownership	-0.156**	-0.009	-0.061*	-0.065***	-0.005	-0.042*	-0.163***	0.073***
	(-2.166)	(-0.247)	(-1.723)	(-2.826)	(-0.471)	(-1.756)	(-3.929)	(2.658)
HHI	0.243	-0.261	-0.090	0.030	-0.036	-0.129	-0.125	-0.121
	(0.629)	(-1.160)	(-0.447)	(0.230)	(-0.510)	(-0.824)	(-0.453)	(-0.885)
HHI Squared	-0.226	0.364	0.168	-0.042	0.062	0.206	0.182	0.150
	(-0.590)	(1.586)	(0.839)	(-0.336)	(0.867)	(1.285)	(0.660)	(1.108)
_cons	-1.794***	-1.382***	-1.301***	-0.453***	-0.220***	-0.706***	-1.621***	-0.518***
	(-7.900)	(-9.700)	(-9.803)	(-6.093)	(-4.689)	(-6.884)	(-8.933)	(-6.052)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
N	40793	40793	40793	40793	40793	40793	40793	40793
R-Squared	0.781	0.814	0.825	0.545	0.657	0.696	0.656	0.776

Table 5 Competition and Innovation Relationship: Acquirers VS. Non-Acquirers

This table reports the cross sectional regression results for the relationship between innovation and competition. The patent and citation measures are aggregated from year t through year t+2. Competition is measured by Text-based Network Industry Classification (TNIC) HHI from Hoberg and Phillips (2015). Subsample1 contains all firm-year that at least one acquisition is announced during the sample period, subsample2 contains firm-year for non-acquirers (no deal announced during the sample period). All control variables are lagged by one fiscal year relative to dependent variables. Other variable definitions are in Table A1. Fixed effects based on year and industries are imposed. Robust standard errors are clustered at the firm level. In parentheses are t-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Subsample1: Bidders Sample			Subsample2: Non-Bidder Sample		
	Ln(Patent)	Ln(Citation)	R&D	Ln(Patent)	Ln(Citation)	R&D
	b/t	b/t	b/t	b/t	b/t	b/t
TNIC-HHI	0.231***	0.307***	-0.056***	0.085*	0.117	-0.067***
	(2.840)	(3.077)	(-16.879)	(1.773)	(1.522)	(-14.103)
Firm Size	0.410***	0.476***	-0.003***	0.151***	0.217***	-0.002**
	(20.146)	(21.262)	(-5.067)	(11.135)	(11.720)	(-2.457)
M/B	0.101***	0.148***	0.005***	0.041***	0.062***	0.007***
	(11.060)	(11.169)	(9.262)	(4.785)	(4.771)	(9.000)
ROA	0.010	0.248*	-0.178***	0.237***	0.388***	-0.222***
	(0.097)	(1.656)	(-20.349)	(3.459)	(3.529)	(-26.253)
Leverage	-0.474***	-0.723***	-0.057***	-0.268***	-0.437***	-0.045***
	(-4.674)	(-5.659)	(-14.290)	(-4.553)	(-4.953)	(-9.457)
R&D	3.192***	4.404***		1.758***	2.498***	
	(12.286)	(12.166)		(9.602)	(8.885)	
Capex	0.937***	1.177***	0.069***	0.428***	0.889***	0.031**
	(3.522)	(3.218)	(5.513)	(3.016)	(3.659)	(2.108)
PPE	-0.142	-0.079	-0.035***	0.037	0.012	-0.034***
	(-0.940)	(-0.434)	(-6.978)	(0.537)	(0.118)	(-5.501)
Firm Age	0.170***	0.210***	-0.002*	-0.069***	-0.065***	-0.000
	(5.277)	(5.076)	(-1.789)	(-3.976)	(-2.618)	(-0.169)
Ins.Ownership	-0.106	-0.076	0.008***	0.060	0.045	0.010***
	(-1.370)	(-0.829)	(3.154)	(0.983)	(0.526)	(2.753)
HHI	-0.330	-0.673	-0.090***	-0.009	0.157	-0.100***
	(-0.806)	(-1.371)	(-6.233)	(-0.036)	(0.409)	(-4.609)
HHI Squared	0.936**	1.427***	0.087***	0.031	-0.116	0.095***
	(2.064)	(2.702)	(6.112)	(0.105)	(-0.284)	(4.047)
_cons	-1.947***	-1.482***	0.097***	-1.234***	-2.206***	0.096***
	(-13.303)	(-8.818)	(17.463)	(-10.399)	(-11.131)	(7.872)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
N	23681	23681	23681	17112	17112	17112
Adjusted R-Squared	0.428	0.390	0.434	0.280	0.250	0.556

Table 6.1 Change in Innovation Quantity after M&A: Multivariate Analysis for Patents

This table reports the panel regression results for change in patenting activities after M&A. The dependent variables are the natural logarithm of patents filed in year t by firm i. "*After*" takes the value of one if the firm-year record is one to three fiscal years after the completion of acquisition(s) and zero for one to three fiscal years before the acquisitions. Innovation output is measured by natural logarithm of patents count. Dummy variable "*Lowmarket*" takes the value of one if the firm's TNIC3-HHI is below the sample median one fiscal year prior to the M&A and zero otherwise. Fixed effects based on year and firm are imposed in all regressions. Other variable definitions are in Table A1. In parentheses are t-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Ln(Patent)	Ln(Patent)	Ln(Patent)
	b/t	b/t	b/t
After	-0.048*	-0.077***	-0.038
	(-1.783)	(-2.830)	(-1.267)
After*Lowmarket			-0.082***
			(-3.161)
Firm Size		0.161***	0.163***
		(8.755)	(8.846)
M/B		0.035***	0.035***
		(5.809)	(5.736)
ROA		-0.125*	-0.115*
		(-1.790)	(-1.646)
Leverage		-0.061	-0.062
		(-0.883)	(-0.897)
R&D		0.595***	0.626***
		(3.119)	(3.279)
Capex		-0.065	-0.053
		(-0.347)	(-0.281)
PPE		-0.084	-0.086
		(-0.744)	(-0.762)
Firm Age		-0.045	-0.040
		(-0.912)	(-0.818)
Ins.Ownership		0.021	0.021
		(0.396)	(0.405)
HHI		-0.301	-0.319
		(-0.930)	(-0.987)
HHI Squared		0.160	0.174
		(0.506)	(0.550)
_cons	0.213***	-0.634***	-0.657***
	(3.504)	(-2.996)	(-3.108)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
N	11554	11526	11526
R-Squared	0.923	0.924	0.925

Table 6.2 Change in Innovation Quality after M&A: Multivariate Analysis for Citations

This table reports the panel regression results for change in patenting activities after M&A. The dependent variables are natural logarithm of all citations received for patents filed in year t by firm i. "*After*" takes the value of one if the firm-year record is one to three fiscal years after the completion of acquisition(s) and zero for one to three fiscal years before the acquisitions. Dummy variable "*Lowmarket*" takes the value of one if the firm's TNIC3-HHI is below the sample median one fiscal year prior to the M&A and zero otherwise. Fixed effects based on year and firm are imposed in all regressions. Other variable definitions are in Table A1. In parentheses are t-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Ln(Citation)	Ln(Citation)	Ln(Citation)
	b/t	b/t	b/t
After	-0.146***	-0.180***	-0.125**
	(-2.740)	(-3.334)	(-2.105)
After*Lowmarket			-0.116**
			(-2.243)
Firm Size		0.269***	0.271***
		(7.363)	(7.425)
M/B		0.069***	0.068***
		(5.725)	(5.672)
ROA		-0.106	-0.091
		(-0.759)	(-0.657)
Leverage		-0.256*	-0.257*
		(-1.853)	(-1.863)
R&D		1.125***	1.169***
		(2.967)	(3.079)
Capex		-0.259	-0.242
		(-0.695)	(-0.648)
PPE		-0.259	-0.262
		(-1.151)	(-1.164)
Firm Age		0.013	0.019
		(0.130)	(0.196)
Ins.Ownership		-0.189*	-0.189*
		(-1.799)	(-1.793)
HHI		-0.477	-0.503
		(-0.743)	(-0.783)
HHI Squared		0.315	0.335
		(0.501)	(0.532)
_cons	0.325***	-1.258***	-1.292***
	(2.689)	(-2.994)	(-3.073)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
N	11554	11526	11526
R-Squared	0.863	0.865	0.865

Table 7 Sample construction process for quasi-experiment

This table provides an overview of the sample of control deals involving biddings withdrawn for different reasons reported by the media press. Original unsuccessful biddings are selected as follows: Deals are announced between 1996 and 2003, transaction value is larger than 1 million, deal form is of "Merger" or "Acquisition of Assets" or "Acquisition of Major Interests", targets are from U.S, bidders are not financial firms, deals attitude of "Friendly", and bidders are U.S public firms. Deal media coverage information is from Factiva and Google News.

<table>
<tr><td colspan="2">270</td><td>All unsuccessful merger bids</td></tr>
<tr><td colspan="2">Less: 181</td><td>Other reasons(Bidder and Target unable to reach agreement on valuation, market expects to fail, differences in growth or strategy, bidder unable to finance the transaction, due diligence revelation about the target's operations, etc.), or not enough information.</td></tr>
<tr><td colspan="3">Deals which failed for reasons exogeneous to R&D of bidder or target party</td></tr>
<tr><td rowspan="3">89</td><td>34</td><td>(i) Objections by regulatory bodies (Department of Justice, Securities and Exchange Commission, Food and Drug Administration, etc.).</td></tr>
<tr><td>26</td><td>(ii) Unexpected legal action or adverse market conditions.</td></tr>
<tr><td>29</td><td>(iii) Competing offers (and news did not report the interest of any of the bidders was due to innovativeness of the target).</td></tr>
</table>

Table 8 Dif-in-Difs Test: Failed Acquirers versus Successful Acquirers

This table reports the panel regression results for the difference-in-differences test regarding change in innovation output after acquisitions. The dependent variables are the natural logarithm of the total patents filed in year t. Dummy variable "*After*" takes the value of one if the firm-year record is one to three fiscal years after the completion/withdraw year of acquisition(s) and zero otherwise. "*Treatment*" is equal to one when the deal is in the treatment group (successful bidders) and zero when it is in control group (failed deals). "*Lowmarket*" takes the value of one if the firm's TNIC3-HHI is below the sample median one fiscal year prior to the M&A and zero otherwise. Fixed effects based on year and firm are imposed. Other variable definitions are in Table A1. In parentheses are t-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Post-deal analysis using year 0 (real deal effective year) as the event year			
	Deals with Bidders from Low market	Deals with Bidders from High market	All Deals
	b/t	b/t	b/t
After	-0.579***	0.024	0.165
	(-2.844)	(0.110)	(0.902)
After*Treatment	0.564***	-0.166	-0.209
	(3.020)	(-0.914)	(-1.195)
After* Lowmarket			-0.609***
			(-2.991)
After*Treatment*Lowmarket			0.493*
			(1.941)
Other Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Deal FE	Y	Y	Y
No. of Observations	213	255	468
Number of Treatment Deals	23	29	52
Number of Control Deals	14	13	27
R-Squared	0.939	0.912	0.919

Panel B: Pseudo-event analysis using year -4 (real effective year minus 4) as the event year			
	Deals with Bidders from Low market	Deals with Bidders from High market	All Deals
	b/t	b/t	b/t
After	-0.339	0.024	-0.453*
	(-0.864)	(0.110)	(-1.864)
After*Treatment	0.410	-0.166	0.319
	(1.052)	(-0.914)	(1.317)
After* Lowmarket			0.004
			(0.013)
After*Treatment*Lowmarket			0.004
			(0.010)
Other Firm Controls	Y	Y	Y

Year FE	Y	Y	Y
Deal FE	Y	Y	Y
No. of Observations	74	255	219
R-Squared	0.963	0.912	0.943

Table 9 Inventor Level Evidence

This table reports the analyses from the inventor-level. Panel A reports the analysis for inventor mobility issue, and stayer productivity change surrounding mergers. Panel B is for leavers and stayers' productivity comparison within firms before mergers. Panel C is for newcomers' productivity comparison after mergers. Panel D is for leavers' productivity change surrounding mergers. In panel A, the dependent variable, "*Present*", takes two values for each inventor: a value one (zero) before the merger event, if the inventor is present (not-present) in any years before the event, and a value of one (zero) after the event, if the inventor is present(not present) in any years after the event. In Panel A, Ln(Patents) (or Ln(Citations)) is the natural logarithm of total patents filed (or total citations received) by inventors within 5 years before/after the mergers. Dummy variable "*After*" takes the value of one for inventor-year after mergers and zero for inventor-year before mergers. "*Lowmarket*" takes the value of one if the firm's TNIC3-HHI is below the sample median one fiscal year prior to the M&A effective year and zero otherwise. Control variables in Panel A include pre- and post-merger bidder's characteristics similar to table 4.1. In panel D, "*Exit from Lowmarket*" takes the value of one if the inventor leaves from a firm whose TNIC3-HHI is below the sample median one fiscal year prior to the M&A effective year, and zero otherwise. "*Join Lowmarket*" takes the value of one if the inventor joins a firm whose TNIC3-HHI is below the sample during fiscal year of the new comer's first patenting activity, and zero otherwise. Fixed effects based on M&A event year and inventor are imposed in Panel A and Panel D. Number of observations reduced in the first two columns in panel A is due to fixed effects imposed, original number of observations is 87794. In parentheses are t-values (or z-values). All standard errors are clustered at inventor-level. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Inventor mobility, and stayer productivity change surrounding mergers.

	Extensive Margin (Inventor Mobility)		Intensive Margin (Stayers Productivity Change Surrounding Mergers)			
	Logit (*Present*=1) z/t	Logit (*Present*=1) z/t	Ln(*Stayer Patents*) b/t	Ln(*Stayer Patents*) b/t	Ln(*Stayer Citations*) b/t	Ln(*Stayer Citations*) b/t
After	0.076**	0.120***	0.020*	0.024**	-0.863***	-0.857***
	(2.558)	(4.004)	(1.777)	(2.169)	(-33.583)	(-33.256)
After* Lowmarket		-0.501***		-0.049***		-0.073*
		(-11.892)		(-3.028)		(-1.881)
Other Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y	Y
N	30192	30192	57404	57404	57404	57404
R-Squared (Pseudo R-Squared)	(0.086)	(0.093)	0.717	0.717	0.738	0.738

Panel B: Stayers VS. Leavers: Pre-merger Productivity Comparison

Inventor from ***Low*** Market Firm	Stayers N=9137	Leavers N=4271	Mean Difference
Ln(Patents)	1.399	1.060	0.339***
			(26.335)
Ln(Citations)	3.682	3.341	0.341***
			(11.867)
Inventor from ***High*** Market Firm	Stayers N=19599	Leavers N=5890	Mean Difference
Ln(Patents)	1.371	1.056	0.315***
			(32.549)
Ln(Citations)	3.670	3.233	0.437***
			(20.197)

Panel C: Newcomers VS. Newcomers: Post-merger Productivity Comparison

	Newcomers in ***Low*** Market Firms: N=2792	Newcomers in ***High*** Market Firms: N=4628	Mean Difference
Ln(Patents)	1.098	1.056	0.042***
			(3.341)
Ln(Citations)	1.908	1.661	0.247***
			(6.083)

Panel D: Leavers Productivity Change Surrounding Mergers

	Ln(Patents) b/t	Ln(Patents) b/t	Ln(Patents) b/t	Ln(Citations) b/t	Ln(Citations) b/t	Ln(Citations) b/t
After	0.204***	0.215***	0.215***	-0.799***	-0.763***	-0.763***
	(13.849)	(11.521)	(11.521)	(-21.229)	(-16.046)	(-16.044)
After* Exit from Lowmarket		-0.027	0.189***		-0.091	0.508***
		(-0.898)	(4.312)		(-1.168)	(4.853)
After* Exit from Lowmarket *Join Lowmarket			-0.331***			-0.916***
			(-6.716)			(-7.552)
Year FE	Y	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y	Y
N	12506	12506	12506	12506	12506	12506
R-squared	0.561	0.562	0.568	0.620	0.620	0.626

Table 10 Probit Regression: Propensity to be acquirer and targets

This table reports the Probit regression result for the firms' propensity to be acquirer and be acquired in the following fiscal year(s) regarding their market concentration distribution. Dependent variable "To be Acquirer" is equal to one if the firm announces a bidding in year t+1 and zero otherwise. "To be Targeted" is equal to one if the firm is acquired in year t+1 and zero otherwise. Other variable definitions are in Table A1. Fixed effects based on year and industry are imposed. Standard errors are clustered at the firm level. In parentheses are z-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	To be Acquirer(0/1)	To be Targeted(0/1)
	z/t	z/t
TNIC-HHI	-0.028	-0.154***
	(-0.579)	(-2.974)
Firm Size	0.188***	-0.019***
	(26.548)	(-2.665)
M/B	0.068***	-0.057***
	(13.100)	(-6.634)
ROA	0.457***	-0.296***
	(6.793)	(-4.350)
Leverage	0.006	0.224***
	(0.105)	(3.708)
PPE	-0.388***	-0.195**
	(-2.707)	(-2.558)
Capex	-0.439**	0.519**
	(-2.228)	(2.424)
R&D	-0.548***	0.593***
	(-7.239)	(4.160)
Firm Age	-0.211***	0.125***
	(-13.912)	(7.345)
Ins.Ownership	0.152***	0.041
	(3.995)	(1.008)
HHI	0.229	0.307
	(1.119)	(1.385)
HHI Squared	-0.324	-0.549**
	(-1.284)	(-2.007)
_cons	-1.295***	-1.595***
	(-8.616)	(-10.898)
Year FE	Y	Y
Industry FE	Y	Y
N	40782	40480
Pseudo R-squared	0.127	0.032

Table 11 Probit Regressions: Acquisition pairing for targets with different market powers
This table reports the Probit regression result for the acquisition pairing issue. Dependent variable equals to one if the target is from the lowest quintile (Column 1) to highest (Column 5) quantile of TNIC3-HHI distribution and zero otherwise. Acq_Q(i)market equals to one if the acquirer is from the i^{th} quintile of the TNIC3-HHI spectrum and zero otherwise. Other variable definitions are in Table A1. Standard errors are clustered at the firm level. Fixed effects based on year and industry are imposed. In parentheses are z-values. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Target is from Q1(0/1)	Target is from Q2(0/1)	Target is from Q3(0/1)	Target is from Q4(0/1)	Target is from Q5(0/1)
	z/t	z/t	z/t	z/t	z/t
Acq_Q1market	1.417***	0.127	-0.226	-1.100***	-0.822***
	(8.711)	(0.830)	(-1.406)	(-6.248)	(-4.883)
Acq_Q2market	0.311*	0.549***	0.242*	-0.412***	-0.655***
	(1.901)	(3.978)	(1.737)	(-3.066)	(-4.539)
Acq_Q3market	0.006	0.222	0.506***	-0.193	-0.492***
	(0.036)	(1.573)	(3.655)	(-1.464)	(-3.428)
Acq_Q4market	0.242	0.108	0.138	-0.093	-0.211
	(1.395)	(0.724)	(0.949)	(-0.699)	(-1.525)
Firm Size	0.083***	0.053*	0.027	-0.035	-0.182***
	(2.631)	(1.754)	(0.935)	(-1.168)	(-4.832)
M/B	-0.092***	0.009	0.007	0.035	0.010
	(-3.050)	(0.341)	(0.276)	(1.295)	(0.270)
ROA	0.234	-0.096	0.042	0.115	-0.321
	(0.833)	(-0.382)	(0.178)	(0.433)	(-1.018)
Leverage	-0.383	-0.385	0.013	0.292	0.310
	(-1.410)	(-1.573)	(0.052)	(1.132)	(1.138)
PPE	0.579**	0.192	-0.103	-0.297	-0.497
	(2.096)	(0.722)	(-0.382)	(-1.006)	(-1.521)
Capex	-1.545	1.111	0.578	0.357	-0.030
	(-1.516)	(1.258)	(0.650)	(0.396)	(-0.026)
R&D	1.433***	0.952**	0.887*	-1.135**	-3.344***
	(2.661)	(2.039)	(1.883)	(-2.005)	(-4.847)
Firm Age	-0.158*	-0.011	-0.056	0.071	0.208**
	(-1.869)	(-0.136)	(-0.714)	(0.892)	(2.212)
Ins.Ownership	-0.033	0.464***	-0.057	-0.149	-0.028
	(-0.197)	(3.307)	(-0.385)	(-0.935)	(-0.167)
HHI	-3.744***	-1.024	0.826	1.271	3.052***
	(-3.580)	(-1.226)	(1.002)	(1.450)	(3.416)
HHI Squared	2.190	0.397	-1.134	-1.289	-2.149*
	(1.245)	(0.302)	(-0.957)	(-1.015)	(-1.715)
_cons	-0.768**	-1.409***	-1.113***	-0.694**	-0.419
	(-2.435)	(-4.878)	(-3.950)	(-2.497)	(-1.230)

Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
N	1379	1379	1379	1379	1379
Pseudo R-squared	0.219	0.053	0.037	0.069	0.157