The Oscar goes to…: Peer pressure, innovation competition, and takeovers

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Abstract: In this paper, we examine how firms react to their competitors' highly publicized achievements in product innovations. We use the renowned annual R&D 100 Award granted by R&D Magazine since 1965, which has come to be known as the "Oscar of Innovation", to measure impactful product innovations by rival industry participants. We find that a firm's propensity to acquire another firm significantly increases following R&D awards won by competitors. A causal interpretation of our finding is supported by our use of the Uniform Trade Secrets Act (UTSA; which exogenously enhances trade secret protection at the state-level) as an instrumental variable, propensity-score matched samples, and comparing the differential effects of winning an award vs. only being selected as a finalist. We also find that this acquisition pattern is stronger for firms with greater industry concentration, more overconfident CEOs, weaker governance, and competitors that do not advertise. These tests suggest that innovation peer pressure drives some acquisitions.

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1. Introduction

Facing fierce competition in the race to develop innovative technologies in today's knowledge economy, firms always risk being left behind and having to catch up with their competitors' path in innovation. Anecdotal evidence suggests that firms can respond to rivals' innovation by using external acquisitions in an imperfectly competitive product market. Cisco's response to Ciena's innovation is a prominent example. Ciena's "100G Coherent Optical Solution" is a technological breakthrough in 100G optical networking and won an "R&D 100 Award" published by R&D Magazine in 2010. This innovation posed a considerable threat to Cisco, one of the largest networking product and service vendors in the world. In reaction to this threat, Cisco acquired CoreOptics and Lightwire, both with advanced technologies in optical networking in 2010 and 2012, respectively, to join the 100G optical networking race.

This Cisco example illustrates one further reason why a firm would choose to acquire innovation via the M&A market rather than invest in in-house R&D: expediency. Because R&D is generally a long-term investment, in-house R&D may take many years to generate innovative outcomes, such as patents and product inventions. When a firm's rival invents a lauded new technology, in-house R&D could be a slow solution to the problem that the firm falls behind in the industry. An acquisition offers a way to accelerate the innovation process for a firm that is faced with threats posed by rivals' new inventions.[1]

While prior studies have found that firms engage in acquisitions in order to gain access to technology developed by target firms (e.g., Blonigen and Taylor, 2000; Bena and Li, 2014; Phillips and Zhdanov, 2013; Lin and Wang, 2016), the underlying cause of these innovation-driven acquisitions remains underexplored. If firms occupy a stable position in a static industry, it would be unnecessary to be engaged in mergers and acquisitions. We propose that the pressure from their rivals' innovative activities, especially technology breakthroughs, is the main motivation for these acquisitive firms for several reasons. Such pressure is more substantial, and may elicit a stronger strategic response, when rivals' inventions are recognized by the media and thus well publicized. Media coverage attracts investors' and analysts' attention and potentially

[1] Moreover, acquiring innovation is more preferable than in-house R&D because the latter is required to be immediately expensed (Francis and Smith, 1995).

leads to requests for managers to formulate an immediate response. Managers may independently perceive peer pressure, or become envious of a peer's achievement, and become motivated to take action even absent pressure from investors or analysts. Moreover, technology breakthroughs may also create new markets that open a window of opportunities for all firms and thus attracts new entrants into the new technology area through M&A.

To empirically test this proposition, we use a well-known innovation award: the "R&D 100 Award" published by R&D Magazine since 1965.[2] This award recognizes the most outstanding 100 technology inventions every year (in any industry or area of technology) that are incorporated into commercial products or services. This award is the most prestigious, and has the longest history (50 years by 2015), of the various innovation awards, and is often regarded as the "Oscar of Innovation" by the community of industrial researchers and managers. This award is listed in the profile or award and recognition section of the websites of many of the world's leading innovative firms, including 3M, United Technologies, Dow Chemical, and Mercedes-Benz. Every year, different organizations including firms, research institutes, and universities apply for this award for their inventions, and their applications are judged by panels consisting of industrial researchers, business consultants, and university professors with expertise in related fields. Based on the judges' recommendations and comments, the editors of R&D Magazine determine the top 100 technologies of the year.

We collect the merger and acquisition (M&A) records of U.S. listed firms from the Securities Data Corporation's (SDC) database. We then combine these M&A records with the merged CRSP/Compustat dataset, enabling us to measure the M&A activities of all U.S. public firms during this period. To identify a firm's competitors / rivals, we use the 10-K Text-based Network Industry Classifications (TNIC) data provided by Gerard Hoberg and Gordon Phillips (see Hoberg and Phillips, 2010) that is available from 1996 to 2013, and define a firm's competitors as the other ten firms with the highest similarity scores to the focal firm in a given year. We then use logit regressions to examine the relation between the awards won by these competitors and the firm's takeover propensity. We find that the probability of a firm acquiring a target increases significantly if its rivals have won innovation awards in the prior three years.

[2] http://www.rd100awards.com.

When the number of award-winning innovative products produced by rivals increases from zero to one, the focal firm's takeover probability increases from 7.6% to 9.2%.

To test the robustness of this baseline result, we also manually collect the lists of competitors (self) disclosed in the 10-K reports of all firms that win the award, or define competitors as firms in the same three-digit SIC code. Consistent results are obtained. Moreover, we use the patents generated by rivals as an alternative measure of the innovativeness of the firm's competitors and find that firms also become more acquisitive when their competitors announce more patents. However, such an effect is weaker than that related to innovation awards. Our baseline result is thus robust to a variety of ways of defining both "rivals" and "innovation."

We are aware of two endogeneity issues. The first issue is reverse causality: rivals may increase their innovative activities to promote creative products that end up winning the R&D 100 Award if they are aware (before a public announcement) that a rival is planning to acquire a target. We do not find this issue convincing because we find that the focal firm's acquisitiveness cannot be explained by rivals' *future* innovation awards. The second (and, likely, more serious) issue is omitted variables, as there may exist a factor that affects both acquisition propensity and innovation among a group of competitors.[3] Even though we have controlled for various industry-level variables that may capture omitted variables at the industry level, including industry-level sales growth, patent counts and growth, and R&D growth, we still cannot rule out this issue. Therefore, we perform two-stage least square regression analysis as well as propensity score matched sampling, and examine the differential effects of rivals winning awards vs. rivals only being on the list of finalists (but not winning).

We use Png's (2016, 2017) index for the legal protection of trade secrets, which is based on state-level laws related to the Uniform Trade Secrets Act (UTSA). This is a valid instrument for the independent variable (i.e., rivals' innovation awards) in our study because it meets both the exclusion and relevancy restrictions. Specifically, the laws governing trade secrets in competitors' headquarter states are likely to be directly related to competitors' inventions but unlikely to be directly related to the acquisitiveness of a focal firm located in a different state

[3] For example, firms in an industry may engage in various means of expanding their businesses when that industry experiences an over-supply of equity financing.

(except via the effect on rivals).[4] We find that rivals' invention awards increase with their own in-state trade secret protection, and that instrumented rivals' innovation awards significantly predict our sample firms' takeover propensity. Further, as suggested by Roberts and Whited (2013) to address endogeneity concerns, we also construct a propensity score matched sample that is balanced in observable characteristics related to takeover propensity. In this propensity-matched sample we continue to find an association between a firm's takeover propensity and the records of rivals winning awards for innovation.

Our final endogeneity test is to compare the effects when rivals win innovation awards vs. being on the list of finalists (but not winning). The premise of this test is that the inventions by non-winning finalists are as (or at least, almost as) influential as the inventions that won the awards, but they lack the publicity effect. So, if our goal is to separate the effect of publicity from the fundamental impact of technological change on an industry, comparing the influence of winners and non-winning finalists is an ideal experiment.

R&D Magazine announced its finalists for the award only since the 2015 award year, therefore we collect that list and track their rivals' M&A activity through December 2016. The small size of the sample makes inference problematic: however, among the 31 firms with rivals winning the award, five (16.1%) engage in acquisitions. On the other hand, amongst the 18 firms whose rivals are on the list of finalists, but do not win, only one firm (5.6%) engages in an acquisition.

After showing that firms' acquisitions are motivated by their rivals' winning innovation awards, we analyze the incentives from both the acquirers' and targets' perspectives. Managers in acquiring firms may engage in award-driven acquisitions due to the second mover's advantage: their rivals' innovation awards may signal or highlight a new market or technology potential, which motivates these firms to seize these opportunities through M&A. Or, such acquisitions may be necessary for managers to avoid obsolescence risk. On the other hand, our finding may be attributed to agency costs as managers may simply react to their rivals' awards because of "peer pressure," which may reduce shareholder value. To test these explanations for our baseline

[4] We restrict rivals to those in different states to the focal firm, to ensure that the trade secret protection effect does not directly influence the focal firm. We also remove observations where the focal firm itself is headquartered in a state that experiences stricter trade secret laws (thanks to the UTSA), to ensure the relevance of this instrument.

result, we examine acquirers' cumulative abnormal returns (CAR) to M&A announcements. We find that M&A deals that appear to be motivated by rivals' innovation awards are associated with negative announcement abnormal returns, controlling for various firm and deal characteristics. Since agency costs predict reduced shareholder wealth for acquirers, our empirical evidence is consistent with this innovation-peer pressure hypothesis.

On the other hand, competitive pressure on *targets* may also explain our findings: some firms become more willing to be acquired by other firms when their rivals experience positive publicity for innovation. To examine this explanation, we test whether the innovation awards of a firm's rivals make a firm more likely to become a target, but we do not find any evidence of this. Thus, it is unlikely that our baseline finding can be attributed to the increased incentives for firms to sell themselves following their rivals' success in innovation.

In our next tests, we find that our baseline results are stronger for acquirers with greater industry concentration, more overconfident CEOs, poorer corporate governance, and rivals without advertising spending. These findings also collectively support an agency cost explanation due to innovation peer pressure, because managers become more aggressive in responding to their peers' success when they only need to focus on a few competitors (in a concentrated industry), when they are more overconfident, when they are not subject to strong corporate governance, when their rivals do not advertise their inventions (making the innovation a relative surprise to the public), and when they are not financially constrained.

Lastly, we examine which types of targets are more likely to be acquired by firms under pressure from the publicized innovation achievements of their rivals. Our finding suggests that firms with rivals winning R&D 100 Awards tend to acquire more innovative targets (i.e., with R&D or patents), which confirms the argument that these acquisitions are designed to buy (rather than build) growth opportunities to enable technological catch-up. We also find that the acquirers that are seemingly motivated by rivals' innovation awards tend to pursue targets in similar product market as their rivals, suggesting that these acquirers choose to confront their rivals.

This study contributes to the existing literature in several ways. First, we closely examine a determinant of M&A activity – the pressure from competitors' innovation achievements. While prior literature has pointed out the importance of acquisitions driven by innovation (Hitt, Hoskisson, Johnson, and Moesel, 1996; Harford, 2005; Sevilir and Tian, 2012; Phillips and Zhdanov, 2013; Bena and Li, 2014), little is known about the drivers of this relation for acquisitions. Using a prominent innovation award that receives much market attention, we are able to capture the peer pressure on firms to react in terms of becoming more acquisitive.

This paper is also related to the influence of product-market competition on M&A activities. Prior studies find that firms become more acquisitive when they are exposed to fierce product-market competition (Karim and Mitchell, 2000; Hoberg and Phillips, 2010). However, any change in such competitiveness often evolves over a long period of time, and the associated industry dynamics and reactions are often difficult to measure precisely. The R&D 100 Award helps us capture more radical changes in product-market competitiveness that are more likely to trigger firms' reactions (by, for example, engaging in M&A).

This paper also adds to the literature on the effect of new product announcements. Prior studies have documented that a firm's market value is negatively impacted by the announcements of new products from its rivals (e.g., Chen, Ho, Ik, and Lee, 2002; Chen, Ho, and Ik, 2005). Our study mainly focuses on how the affected firm reacts to such challenges by acquiring more innovative targets. More importantly, we use a well-publicized award about product innovation that will have a substantial and long-lasting impact on the affected firm (prompting the firm to react via takeovers to ensure their long-term competitiveness) rather than merely causing short-term stock price fluctuations.

The remainder of this paper is organized as follows. In Section 2, we describe our data, variable construction, and summary statistics. Section 3 presents our empirical results, robustness checks, and endogeneity tests. Section 4 provides additional tests for M&A announcement effect and conditional effects, and Section 5 examines the choice of targets. Section 6 concludes.

2. Data, variable and summary statistics

2.1. Data

We manually collect the list of all products that have received the "R&D 100 Award" published by *R&D Magazine* from 1965 to 2014. The magazine invites firms, research institutes, or individuals to submit their newly commercialized inventions to the magazine, and the magazine editors (with the advice of outside experts) select the 100 winning inventions and announce them in the magazine published in summer or fall. The R&D 100 Award principally covers inventions that are newly introduced to the market in the prior one to two years. As stated in the R&D 100 Award webpage for the 2016 award, "*To be eligible for R&D 100 Awards consideration, your product or service must have entered the marketplace between January 1, 2015 and March 31, 2016*."[5] The probability of winning the award is low. Taking Dow Chemical Company as an example, among its approximately 5,000 newly introduced products every year, 21 are listed as finalists for the award in 2015, and just 6 won the prize (including products co-developed by Dow Chemical).[6]

Given the fact that there are so many different products being judged by the editors and industry experts every year, there is no further ranking within the selected 100 inventions. Each award-winning invention is attributed toward one or multiple main contributors (the producers) as well as zero to multiple co-developers. In Table A1 in the Appendix, we list (in alphabetical order) the inventions that won the R&D 100 Award and their contributors in the year 2014. These 100 inventions are (co-)developed by 103 firms (88 unique firms), 46 public firms (30 unique public firms), 49 laboratories (21 unique laboratories), and 12 universities (11 unique universities). The list suggests the active roles played by firms, universities, and research institutes in innovative activities.

The long history of these awards encompasses many of what once were cutting-edge technologies such as halogen lamps (1974), the fax machine (1975), and HDTV (1998). Also, this award is regarded as the most prestigious invention award, often known as the "Oscar of

[5] The complete application information for the 2016 award is available at: https://www.advantagemedia.com/sites/default/files/RD%20100%202016%20Form%20Preview.pdf

[6] The *R&D Magazine* did not release the finalists until 2015.

Invention", and has been wide recognized by leading innovators in the industry.[7] We find that the majority of award-winning inventions are consumer product inventions: this is probably due to the fact that production process improvements are often proprietary (i.e., kept as business secrets). Nevertheless, some inventions related to process innovation, such as computer software and new equipment, are recognized by the award. Overall, the R&D 100 Award can be regarded as a well-publicized event that brings the market attention to some particularly innovative products and services newly introduced to the market.

In Table A2 in the Appendix, we document the industry distribution of all award-winning public firms in the period 1980 and 2014. This table suggests that the award has been granted to firms in many industries and thus allows us to analyze its effect across different segments. In Table A3 in the Appendix, we list the frequency distribution of public firms that have ever won the award at least one time in the period between 1980 and 2014. We find that Lockheed Martin won 131 awards and Dow Chemical won 62 awards. More importantly, amongst all winners, 63% of public firms only win the award once. In addition, 15%, 6%, and 3% lead this rank by winning the awards for 2, 3, and 4 times, respectively. This distribution speaks to the difficulty (and rarity) of winning an R&D 100 Award, and justifies our use of these awards as significant events that credibly prompt a rival reaction.

To examine the effect of peer pressure for firms with rivals that recently win this award, we first have to define "rivals." We use the 10-K Text-based Network Industry Classifications (TNIC) data provided by Gerard Hoberg and Gordon Phillips (see Hoberg and Phillips, 2010) to

[7] For example, on November 5, 2014, Mercedes-Benz announced that "*The US tech-specialist magazine, R&D Magazine, chose NANOSLIDE® as one of the 100 most important high-tech products launched in 2013. NANOSLIDE® is an innovative cylinder coating technology which reduces friction in combustion engines. The prestigious R&D 100 Award, also known as the 'Oscars of Invention', will be presented to Mercedes-Benz and partner Heller Maschinenfabrik GmbH this Friday, November 7th in Las Vegas (USA).*" On November 7, 2014, United Technologies announced that "*United Technologies Research Center (UTRC), the research and innovation arm of United Technologies Corp. (NYSE: UTX), has been recognized by R&D Magazine as a recipient of the publication's prestigious R&D 100 Award for two breakthrough eco-friendly technologies: EcoTuff® corrosion inhibitor and a portable aluminum deposition system (PADS)…. R&D Magazine featured its R&D 100 Awards -- known as the "Oscars of Innovation" -- and 2014 recipients, including UTRC's EcoTuff and PADS technologies, in its Sept./Oct. 2014 issue.*" Other awards for commercialized innovations include Edison Best New Products Award (awarded since 1987) and The 100 Greatest Innovations of the Year from Popular Science Magazine (awarded since 1988).

construct portfolios of rivals for our baseline analysis.[8] Following their suggestion, we define a firm's rivals as the ten firms with the highest similarity scores to the focal firm in a given year.[9] The Hoberg and Phillips product similarity index is available from 1996 to 2013.

Moreover, we consider two alternative approaches to define "rivals." First, we manually collect the competitors mentioned in the 10-K reports of each firm that has won the award. For a firm that wins the award in a particular year, we manually collect the list of competitors disclosed in its 10-K report for that year and in the following two years. Based on the idea that the rival relation is mutually defined, we assume that a competitor of the award-winning firm considers the award-winning firm to be a rival. We use this approach to define rivals from 1992, the first year in which such data is available in the Edgar database of the U.S. Securities and Exchange Commission (SEC). Second, we define "rivals" as all firms in the same three-digit SIC industry as an award winner. This approach gives us the longest sample period, as we are able to identify rivals from 1980 onwards.

We then collect M&A data from 1981 to 2015 from the Securities Data Company's (SDC) U.S. Mergers and Acquisitions database. We exclude financial firms (identified by first digit of SIC code 6), American depositary receipts, closed-end funds, non-U.S. firms, and real estate investment trusts from our analysis. We measure a firm's reaction to the peer pressure induced by a rival winning an award by whether it has made a successful or unsuccessful attempt to acquire another firm in an M&A deal.[10]

To measure patenting activities, we first collect data on all patents granted by the United States Patent and Trademark Office (USPTO): these data are from Noah Stoffman's website (as in Kogan et al., 2016). The dataset includes the filing dates, grant dates, and the CRSP firm identifiers of the patent assignees that are U.S. public firms for all utility patents in the period

[8] The data are available at http://hobergphillips.usc.edu/. We thank Gerard Hoberg and Gordon Phillips for making the data publicly available on the website.
[9] We also select five, three or one rival(s) that have nearest pairwise Hoberg and Phillips (2010) similarity scores in order to identify the rival(s), and our results remain quantitatively similar.
[10] We obtain similar results if we restrict our sample of acquisitions to only *successful* M&A deals.

1926-2010. Since the M&A data we collect ends in 2015, we then extend the patent data to include all patents granted to public firms by the end of 2014 using the Google Patent database.[11]

We also collect the financial and equity data for all public firms from the Compustat and Center for Research in Security Prices (CRSP) databases. We exclude American depositary receipts, closed-end funds, non-U.S. firms, and real estate investment trusts from our analysis. Since the TNIC data we use to define rivals is only available from 1996 to 2013, the sample we use in our baseline analysis includes public firms' innovation awards and granted patents from 1996 to 2013 and M&A activities from 1997 to 2014.[12] The final sample consists of 68,057 firm-year observations for 8,999 unique firms. The key variables used in this paper are defined in Table A4 in the Appendix.

2.2. Variables and summary statistics

We present summary statistics for the relevant variables in Table 1. To measure firm *i*'s peer pressure from rivals' innovation awards in year *t*, we use the number of awards received (collectively) by its rivals in a one-year (year *t*) or three-year (i.e., year *t-2* to year *t*) period. When we define "rivals" using the ten firms with the highest similarity scores in the Hoberg and Phillips (2010) data, we find that the average numbers of rivals' awards in the year and three years are 0.08 and 0.24, respectively. We also note that even the 90th percentile is equal to zero due to the difficulty of winning an R&D 100 Award. In particular, 4.4% (8.6%) of firm-year observations have rivals winning at least one award in the one-year (three-year) period. When competitors are defined based on firms' 10-K reports and the three-digit SIC code (not tabulated in Table 1), we find that the averages of rivals' awards in the three years are 0.04 and 1.12, respectively. In addition to rivals' awards, we also control for the awards won by the focal firm in our analysis. The average of innovation awards for the firm itself in the three years is 0.02.

[11] The most critical task in extending the patent data is to identify whether a patent assignee is a public firm, and to assign the CRSP firm identifiers to it. For each patent assignee in the post-2010 data, we use a name-matching algorithm to match its name and location to a pool of names and locations that have appeared as assignees of patents listed in Kogan et al. (2016).

[12] Later in the paper we perform a robustness test where we identify rivals as firms in the same three-digit SIC industry. This test uses an extended sample of U.S. listed firms between 1980 and 2014.

Table 1 also shows that 8.2% of sample firm-year observations have attempted to initiate an acquisition in a year and 7.3% (not tabulated) have successfully completed at least one. Summary statistics of other firm and industry characteristics that we control for are also presented in the Table 1, including Tobin's Q, Property, Plant, and Equipment (PPE), cash ratio, size, leverage, return-on-assets (ROA), sales growth, R&D-to-assets ratio, the number of patents granted, industry M&A indicator, sales concentration (measured by the Herfindahl-Hirschman Index), the industry-level sales growth rate, and industry-level number of patents. Detailed definitions of all variables are presented in Table A4 of the Appendix.

3. Empirical results

3.1. Logit regression of takeover propensity

In our baseline analyses, we perform logit regressions to investigate the relation between a firm's probability of being involved in a takeover (as the acquirer) and the number of its rivals' innovation awards. We follow the logit regression model in Bena and Li (2014) and use the logarithmic value of one plus the number of rivals' innovation awards in year *t* or year *t-2* to year *t* (*log(1 + number of rivals' innovation awards)*) as our main explanatory variable. The dependent variable is *M&A indicator*, which equals one if a firm announces a successful or unsuccessful M&A deal in year t+1, and zero otherwise.[13] Due to the availability of TNIC data, the sample period is 1997 to 2014 for M&A activity and 1996-2013 for *log(1 + number of rivals' innovation awards)* and the control variables. Specifically, we estimate the following logit model:

$$P(\textit{M\&A indicator} = 1) = \theta(a_0 + a_1\, \textit{log(1 + number of rivals' awards)} + \boldsymbol{\beta' X} + e), \qquad (1)$$

where θ is the cumulative density function of logistic distribution. ***X*** represents a set of control variables, including the logarithmic value of one plus the number of the focal firm's innovation awards in year *t-2* to year *t*, Tobin's Q, PPE, cash ratio, size, leverage, ROA, sales growth, R&D-to-assets ratio, patent count, an industry M&A indicator, HHI, the industry-level sales growth

[13] Our results are quantitatively similar if we exclude incomplete M&A cases from the logit regression analysis. We also perform probit regression analysis and results are not changed.

rate, and the industry-level patent count. All control variables are measured in year *t*. All regressions include year and industry (two-digit Standard Industrial Classification (SIC) code) fixed effects (Harford, 2005). Standard errors for computing *t*-statistics are clustered at the industry-year level to correct for estimation errors common in each industry-year pair.[14]

Table 2 presents the logit regression results, where Model 1 includes the focal firm's innovation awards, Tobin's Q, PPE, cash ratio, size, leverage, ROA, sales growth, R&D-to-assets ratio and patent count as control variables.[15] The coefficient of our key variable, *log(1 + number of rivals' innovation awards)* in the past three years, is 0.1016, statistically significant at the 5% level. This suggests that a firm's acquisitive appetite significantly increases when its rivals have won more innovation awards. This coefficient estimate is also economically substantial. When the number of award-winning products produced by rivals increases from zero to one, the focal firm's takeover probability increases from 7.6% to 9.2%, and such an increase in probability is commensurate to 19.6% of average acquisition probability for a firm/year (19.6% = (9.2%−7.6%) / 8.16%).

Model 2 further controls for four industry-level variables: the industry M&A indicator, HHI (market share concentration), the industry-level sales growth rate, and the industry-level number of patents. The coefficient on our key variable of interest remains positive and significant. Specifically, the coefficient on *log(1 + number of rivals' innovation awards)* is 0.1021, which is significant at the 5% level. In terms of economic significance, when the number of rivals' awards increases from zero to one, the focal firm's takeover probability increases from 7.6% to 9.2%, and such an increase in probability is commensurate to 19.6% of average acquisition probability. We have also added more industry-level innovation variables (e.g., patent growth, R&D to assets and R&D growth) to the logit regression to ensure our result is not driven by fundamental industry innovation (which could explain both R&D 100 awards *and*

[14] We also consider two-way clustered standard errors (by year and industry) to compute *t*-statistics in the logit regression analysis, and find that the coefficient of *log(1 + number of rivals' innovation awards)* is still significant at the 10% level.

[15] We try to control for the patent self-cites ratio in the logit model as a robustness check. The coefficient on our variable of interest is statistically unchanged, although the sample size is reduced due to data availability. Moreover, we replace patent count by patent citations or International Patent Classification (IPC)-adjusted patent citations as a control variable, and our results are unchanged. Finally, we control for market share of bidder. Although market share is highly correlated with firm size, our baseline result still holds after adding market share to the regression models.

greater M&A activity in the industry). Our results (presented in Table IA1 in the Internet Appendix) remain unchanged after adding all these additional controls.

The coefficient estimates on the control variables are largely consistent with prior studies. We find that firms with higher equity market valuations (Tobin's Q) are more acquisitive, as are large firms and those that are more profitable. In addition, a firm's takeover propensity is negatively associated with leverage and R&D (where the former affects financial constraints and the latter likely represents internally generated growth options).

In Models 3 to 4, we adopt the logarithmic value of one plus the number of rivals' innovation awards in year *t* as the explanatory variable. Even though the proportion of rivals that have won innovation awards decreases because of the shorter time span, the effect of rivals' innovation awards on acquisition remains statistically significant. In fact, the coefficients on *log(1 + number of rivals' innovation awards)* in these two models based on year *t* are higher than their counterparts in Models 1 and 2. This finding is intuitive because current events likely have greater influence on the behavior of managers.

We also use the number of rivals' innovation awards in year *t* + 1 as an explanatory variable because it is likely that the focal firm bids on some targets immediately after the rivals win innovation awards, and two events take place at the same year. In the Internet Appendix, we present the results in Table IA2, and our finding remains unchanged.

3.2. Robustness tests

In addition to the product similarity index from Hoberg and Phillips (2010), we consider two alternative approaches to identify rivals of the sample firm. First, for every firm that wins an R&D 100 award in a particular year, we manually collect the list of competitors disclosed in their 10-K reports for that year and in the following two years. Based on the idea that the rival relation is mutually defined, we assume that a competitor of the award-winning firm treats the award-winning firm as a rival. Among the 202 firms that have ever won the award in the sample period 1993 to 2013, we find that the average number of "competitors" defined in this way (through 10-K searches) is 9.27 per firm-year observation. Although the information about competitors in 10-K reports could be self-selected, it offers us an easy-to-understand (and perhaps more precise) way to define “rivals.” The empirical results presented in Table IA3 of the Internet Appendix are consistent with our baseline model in Table 2.

Next, we define competitors as firms in the same three-digit SIC code industry as the focal firm, since SIC code matching is the most popular (but rough) approach to identify competitors or rivals (e.g., Sundaram, John, and John, 1996; Massa, Rehman, and Vermaelen, 2007; Hertzel and Officer, 2012; Aghion, Van Reenen, and Zingales, 2013). In addition, since our main test based on Hoberg and Phillips’ (2010) TNIC data is restricted to 1996 to 2013, the use of SIC-defined competitors enables us to use a much larger sample because we can extend the sample period back to the early 1980s. Due to the fact that SDC data covers M&A activity starting in 1981, we use the 1981-2015 period to measure M&A activity and the 1980-2014 period for our key independent variable of interest (*log(1 + number of rivals' innovation awards)*) and the control variables. Table IA4 of the Internet Appendix reports the logit regression analysis with this extended sample, and the effect of rivals’ innovation awards on the focal firm’s takeover propensity remains strong.

We also consider using rivals’ patenting performance as the source of innovation peer pressure or competition intensity. We replace *log(1 + number of rivals’ innovation awards)* with *log(1 + number of rivals' patents)* as our main explanatory variable, the number of rivals’ patents is defined analogously to the number of rivals’ awards. As reported in Table IA5 in the Internet Appendix, the coefficient estimates of *log(1 + number of rivals’ patents)* are positive, confirming our main argument. In particular, when we incorporate both *log(1 + number of rivals’ patents)* and *log(1 + number of rivals’ innovation awards)* in a regression model, we find that the coefficient estimate of *log(1 + number of rivals’ patents)* is positive but becomes insignificant, whereas the effect of *log(1 + number of rivals’ innovation awards)* remains significantly positive.

This patent effect is found to be economically smaller than the estimated impact from the winning of an R&D 100 Award. On the one hand, we provide consistent evidence for the influence of innovation peer pressure or competition pressure using patent data. On the other hand, the finding that an R&D 100 Award has a stronger effect on a rival’s takeover propensity than patent performance does is consistent with the argument that very well-publicized events necessitate managers make more immediate responses. Another possibility is that it takes time to commercialize patents; thus, peer pressure from patent-related information does not mandate an immediate response in the way that award-related information does.

3.3. Endogeneity tests

We recognize that our findings reported in Table 2 may be subject to two types of endogeneity and that we cannot easily treat the statistical association as a causal relation. The first is reverse causality, i.e., the focal firm's future takeover probability increases its rivals' innovation awards but not the other way around. One possibility is that rivals accelerate their innovative activities that end up winning the R&D 100 Award when they are aware (before the public announcement) that the focal firm is planning to acquire a target. However, we do not find this explanation convincing because when we do not find that *log(1 + number of rivals' innovation awards)* in year *t+2* explains a firm's acquisitive activities in year *t+1* in Table IA2 in the Internet Appendix. This finding contradicts to the reverse causality argument.

The second issue is omitted variables. That is, there could exist a factor that affects both acquisition likelihood and innovation among a group of competitors. For example, firms in an industry may engage in various means of expanding their businesses (including producing more inventions or acquiring more targets) when that industry experiences an over-supply of equity financing. However, as shown in Table 2 and Table IA1 of the Internet Appendix, we obtain consistent results when we control for various industry-level variables that may capture omitted variables at the industry level, including industry-level sales growth, patent counts and growth, and R&D growth.

To further address these endogeneity issues, however, we examine a two-stage least squares (2SLS) regression analysis using competitors' state-level trade secret protection as an instrumental variable (IV). The IV we use is Png's (2016, 2017) index for the legal protection of trade secrets, which is based on state-level laws related to the Uniform Trade Secrets Act (UTSA). These laws are exogenous to most economic activities and positively influence the commercialization of inventions, as shown in Png's papers.[16] To ensure that this IV does not directly affect the focal firm's M&A propensity, we restrict rivals to those headquartered in *different* states to the focal firm. In addition, we impose the restriction that the focal firm's headquarter state does not experience concurrent increases in the UTSA index. Under the setting of cross-state competition, competitors' state-level trade secret protection is a valid instrument for our explanatory variable (i.e., rivals' innovation awards) because it likely meets both the exclusion and relevancy restrictions. Specifically, the laws governing trade secrets in competitors' headquarters states are likely to be directly related to competitors' innovation but unlikely to be related to the focal firm's acquisitiveness (except via the effect on rivals).

Table 3 reports the results from the 2SLS analysis, where we focus on the full regression setting that includes industry-level control variables as in Model 2 of Table 2 to save the space. We consider two versions of a UTSA-based IV: the first is the average of the UTSA indexes of all rivals' states in a year (Models 1 and 2 in Table 3). We use rival's innovation awards in the prior three years (year *t-2* to year *t*) as the explanatory variable in Panel A and adopt rival's innovation awards in the prior one year (year *t*) as the explanatory variable in Panel B.

Since the focal firm's innovative activities may be affected by omitted factors, we do not include the focal firm's awards, R&D, and patents in the first stage regression of Model 1;[17] on the other hand, we keep these variables in the first stage of Model 2. In stage 1 of Model 1 in Panel A, the coefficient of competitors' (state-level) *average UTSA* score is 0.32, which is significant at the 1% level. This implies that the average UTSA index in competitors' states is a relevant IV for competitors' innovation awards. In stage 2 of Model 1, we find that instrumented rival innovation awards significantly predict our sample firms' takeover propensity, where the coefficient of instrumented *log(1 + number of rivals' innovation awards)*^ is 2.06, statistically significant at the 1% level. The instrumented *log(1 + number of rivals' innovation awards)*^ is purely based on the predicted value from the first stage regression (i.e., dependent on only the IV and other control variables), and is thus free from the reverse causality and omitted variables

[16] By the end of 2010, 44 states have enacted legislation consistent with the UTSA. The first state was Minnesota (1980), and the last state was Wyoming (2006). While California enacted UTSA in 1985, New York and Massachusetts have not as of the end of 2010.

[17] Such a setting is adopted to ensure that the instrumented *log(1 + number of rivals' innovation awards)* will not contain any component related to a firm's realized innovation performance as well as expected innovation opportunities.

problems discussed earlier. Model 2 uses a different regression for stage 2, but results are unchanged.

The second version of the UTSA-based IV is the average of the sum of state-level common law indexes (reflecting the protection for trade secrets before the enactment of the UTSA) and the UTSA indexes (reflecting the increase in the protection for trade secrets after the enactment). Similarly to Models 1 and 2 of Panel A, Model 3 does not include the focal firm's awards, R&D, and patents in the first stage regression but Model 4 does. In stage 1 of Model 3, the coefficient on competitors' (state-level) *average UTSA plus common law* score is 0.28, again significant at the 1% level. In stage 2 of Model 3, the coefficient on the instrumented *log(1 + number of rivals' innovation awards)*^ is 2.50, which is again significant at the 1% level. Similar results are obtained in Model 4. Moreover, when we use rivals' innovation awards in the prior one year in Panel B, our results are statistically consistent. Accordingly, the results reported in Table 3 suggest that our fundamental finding, that innovation awards won by rivals appear to increase the acquisitive appetite of a firm, cannot be simply attributed to endogeneity issues.

To further address the omitted (but *not* unobservable) variable issue, as suggested by Roberts and Whited (2013) we construct a propensity score matched sample that is balanced in observable characteristics related to takeover propensity. We follow Bena and Li (2014) and construct the propensity score for matched firms. More precisely, for each acquirer in an M&A deal in year *t*+1, we find other firms in the same industry (two-digit SIC code) and then match on the propensity to conduct an acquisition in year *t*+1. We estimate propensity scores using a model that includes size and the ratio of book equity to market equity in year *t* and only for firms that do *not* announce acquisition in the three-year period prior (i.e., have not acquired any target recently). We select the five firms that are in the same industry and have the closest propensity score to the acquiring firm.[18]

Table 4 reports the results from the logit regression analysis using the propensity matched sample, where we use rival's innovation awards in the prior three years as explanatory variable in Panel A and adopt rival's innovation awards in the prior one year as explanatory variable in

[18] We also select one, three and ten matched firms by matching propensity scores, and the empirical results remain consistent.

Panel B. The coefficients on the key explanatory variable *log(1 + number of rivals' innovation awards)* are around 0.12 in Models 1 and 2 of Panel A, and significant at the 1% level. Moreover, the coefficients on rivals' innovation awards are similar to those in our baseline results reported in Table 2. These findings suggest that amongst a set of firms that are in the same industry and have similar predicted acquisition propensity, the firms with rivals winning innovation awards are more likely to become acquirers in the next year.

As an alternative matching criteria, we again match by industry but then estimate the propensity score matching model using size, the ratio of book equity to market equity, sales growth, granted patents, and ROA. Again we find the five closest matches to the acquiring firm, and call this the "Propensity matched sample (B)" in Table 4. Using this sample we continue to find that rivals' innovation awards positively explain the focal firm's acquisition (see Models 3 and 4 in Table 4). In Panel B of Table 4, our results remain when using the rivals' innovation awards in the prior year as the explanatory variable. In short, the positive relation between acquisitions and competitors' innovation awards still holds in a more balanced sample in which the sample firms are more homogenous in terms of industry and their propensity to engage in acquisitions.

Our last endogeneity test is to compare the effect on rivals from a firm winning an award vs. only being on the list of finalists. If we assume that the inventions by the finalists are as (or, at least, almost as) influential as the inventions that won an award, examining rivals' reactions to R&D 100 Award winners and comparing those to rivals' reactions to firms being on the list of finalist (without winning) may be an effective way to isolate the impact of the publicity from the award. In other words, one of the sources of endogeneity that concerns us in this context is the possibility that fundamental innovation in the industry (i.e., technological shock) is driving both award winning and M&A activity: comparing the rival reactions to winners vs. finalists holds constant the amount of innovation (more or less) and enables us to focus on the impact on rivals of publicity (and innovation peer pressure).

As R&D Magazine started to announce its list of finalists for the award only in 2015, the sample we have to work with is small, which impairs inference. We collect the list of finalists for the R&D 100 Award in 2015 and track their rivals' M&A activities in 2016. In 2015 there are

181 finalists for the award that did not win. We identify their rivals using the Hoberg and Phillips product similarity index from 2013 (the last year for which these data are currently available). In Table A5 in the Appendix we describe the acquisition activities of affected firms that have at least one rival winning the award or on the list of finalists in 2015. Among the 31 firms with rivals winning the award, five (16.13%) engage in an acquisition in 2016; on the other hand, among the 18 firms with rivals that are finalists only (and did not win), only one firm (5.7%) engages in an acquisition. Although the sample size is regrettably too small to perform a statistical (Chi-square) test, the difference in proportions is economically large, and suggestive of a causal effect of R&D 100 Award on public firms' acquisition tendency via the publicity surrounding the award and the innovation peer pressure that it engenders.

4. Explanations for empirical findings

4.1 Acquirers' incentives

So far we have shown that firms' acquisitions appear to be triggered by their rivals' innovation awards. We propose two possible explanations for why managers engage in acquisition to respond to their peers' award-winning events: agency and a second mover's advantage. First, the traditional agency hypothesis (following papers such as Masulis, Wang, and Xie (2007)) suggests that managers engage in empire-building acquisitions that destroy value for their shareholders. When peers receive innovation awards, ambitious managers motivated by innovation peer pressure may take immediate action (i.e., taking over other firms) even though such action is not value-enhancing. The value reduction is likely because non-cooperated firms may over-invest in R&D under a Pareto equilibrium (Mortensen, 1982). Alternatively, managers may try to exploit a second mover's advantage in a technology race. Peers' winning innovation awards may signal the market or technology potential for managers to focus on. Affected firms may seize new technologies or markets through M&A, and, even as runners-up in the technology race, in part enjoy Ricardian rents. Or, managers may observe competitive pressure and have to react to such events by acquiring another firm. Either way, under this second hypothesis, their acquisitions are rational, necessary choices and should not destroy shareholder value.

To attempt to distinguish between these two explanations for acquirers' incentives, we examine the announcement returns of affected M&A deals. We calculate 5-day (-2, 2) announcement abnormal returns for acquirers using a market model as the benchmark for normal returns. We estimate the market risk of a stock (i.e., beta) using daily returns between day -200 to -11.[19] We then regress the 5-day cumulative abnormal returns (CAR) on the number of innovation awards of rivals, controlling for some of the variables in Table 2 and other firm and deal characteristics (e.g., free cash flow, stock run-up, indicators for payment methods, private target and tender offers, and relative deal size). Year and industry fixed effects are also included in the regression.

Table 5 presents the regression results for all M&A announcements in our sample period. When we control for firm characteristics in Model 1, the coefficient on *log(1 + number of rivals' innovation awards)* is -0.0050, which is statistically significant at the 5% level. In Model 2, we incorporate industry-level control variables in the regression, and find that the coefficient on rivals' innovation awards is -0.0051 with again statistical significance at the 5% level. In Model 3, we further incorporate Gompers, Ishii, and Metrick's (2003) G-index, and find a similar significant coefficient on rivals' innovation awards. Moreover, the results of using innovation awards in the prior one year (instead of three) are consistent with these findings, and they are presented in Table IA6 of the Internet Appendix. All these estimates suggest that investors react negatively to acquisitions that appear to be driven by pressure from rivals' innovation awards.[20] As a result, our empirical evidence suggests that the award-driven acquisitions are value-destroying on average, which is consistent with the agency story and attributes our baseline finding to innovation peer pressure.

4.2 Targets' incentives

Another explanation for our baseline finding is that some firms become more willing to be acquired when they discover that their rivals have won innovation awards. Such a phenomenon may occur when these potential targets are financially constrained and thus must

[19] We also measure CARs over other windows, for example (-1, 1) and (-3, 3), and our results are quantitatively unchanged.
[20] In further (unreported) analyses, we find that neither the premium that acquirers pay for targets nor acquirers' post-merger changes in operating performance (i.e., realized synergies) are significantly associated with rivals' innovation awards.

resort to external financial support (via acquisition) or they are behind in a technology race and looking for synergy after being acquired. To examine this explanation, we test whether the innovation award of the target firm's rivals affects the likelihood of being a takeover target. We have to focus on our sample on publicly traded target firms because we do not have the TNIC information for private target firms. In Table 6, we report the results from a logit regression analysis in which the dependent variable is the occurrence of a sample firm becoming a target of an announced M&A deal and all independent variables are the same as in Equation (1). We find that the coefficient of *log(1 + number of rivals' innovation awards)* is statistically insignificant, meaning that firms are not more likely to be bought when their rivals win innovation awards.

4.3 Factors influencing acquisitiveness

To further examine the explanations for our baseline results, we propose that the effect of rivals' innovation awards on the focal firm's acquisition decision depends on five conditional factors (or channels): product market concentration, CEO overconfidence, corporate governance, and advertisement expenditure. We report the results of using rivals' innovation awards in the prior three years in following tables, and present the results of using innovation awards in the prior one year in Table IA7 of the Internet Appendix to save space.

The first dynamic that we examine is industry concentration. Firms in a more concentrated industry tend to react more aggressively to behaviors by their industry peers, as evidenced by studies examining leverage, repurchases, and R&D investment (e.g., Lang and Stulz, 1992; Massa, Rehman and Vermaelen, 2007; Chen, Chen, Liang and Wang, 2013). On the other hand, firms in an industry with too many competitors may find it difficult to monitor and respond each competitor's action. We thus propose that focal firms respond more aggressively to innovation awards of their rivals if the industry is more concentrated. In a more concentrated industry, a firm is expected to pay more attention to each competitor. On the other hand, it is almost impossible for a firm in a competitive market with many rivals to respond to all competitors' actions. We follow the existing literature and measure the extent of market concentration using the Herfindahl index (HHI), which is the sum of squared market shares (firm sales-to-industry sales ratio) in a three-digit SIC industry. Higher HHI implies higher product market concentration.

Panel A of Table 7 shows that in the low HHI subsample, the coefficients on *log(1 + number of rivals' innovation awards)* are statistically insignificant. For the high HHI subsample, however, the coefficients on *log(1 + number of rivals' innovation awards)* are around 0.18 and statistically significant at the 1% level. We also examine the economic significance. When the number of awards won by rivals increases from zero to one, a firm's takeover probability increases from 7.1% to 10.5% if they are in the high HHI (i.e., concentrated) subsample.

In addition, we identify competitors for each focal firm using Hoberg and Phillips' (2010) product similarity scores, and calculate sales-based HHI's using groups of the ten closest competitors according to that data source. Results for the subsamples sorted by the HHI using Hoberg and Phillips-defined competitors are presented in Panel B of Table 7. Again, for the low HHI subsample, there is no significant impact of rivals' innovation awards on the focal firm's acquisition behavior. On the other hand, in the high HHI subsample the coefficients on *log(1 + number of rivals' innovation awards)* are around 0.13 in both models, and are both significant at the 5% level.

Table 7 therefore suggests that firms in more concentrated industries respond more aggressively to award-winning innovation by rivals (by engaging in takeover activity).[21] This finding supports the innovation peer pressure explanation because managers have limited attention, and thus react more strongly to peers' events when there are fewer peers to keep track of (i.e., in concentrated industries). On the other hand, the second mover's advantage explanation does not have a clear prediction in terms of industry concentration.

The second factor that we consider is CEO overconfidence. More overconfident managers believe in their superior abilities, and thus should be eager to react to peer pressure. Building off the literature that demonstrates that overconfident CEOs more actively engage in acquisitions in general (Malmendier and Tate, 2008), we hypothesize that firms with

[21] Furthermore, we employ several other methods to identify industry concentration as robustness checks. First, we identify industries in the traditional manner, using two-digit SIC codes, and calculate HHIs that way. Second, we use the fixed industry classification from Hoberg and Phillips, available at their website (http://hobergphillips.usc.edu/), where we employ icode 25 or icode 50 to compute HHI. Third, we gauge the median of rivals' Lerner indices **(**Aghion, et al., 2013**)** as a measure of competition. In all these permutations, we continue to find that focal firms are more acquisitive when their rivals win more innovation awards, especially when the market is less competitive (i.e., more concentrated).

overconfident CEO are especially more likely to acquire others when their firms are faced with threats from their rivals' awards for inventions. We define an overconfident CEO if they hold stock options that are more than 67% in the money (Malmendier and Tate, 2005; Campbell, et al., 2011). As a robustness check for this 67% in-the-money approach, we use the retention of 100% in-the-money options to identify CEOs with relatively high optimism (Campbell, et al., 2011).

We report logit regression results for subsamples sorted by CEO overconfidence using the 67% (100%) cutoff for moneyness in Panel A (Panel B) of Table 8. In Panel A we find that for the firms with overconfident CEOs the coefficients on our key independent variable (*log(1 + number of rivals' innovation awards)*) are both around 0.26, and are both statistically significant at the 1% level. The economic significance is also substantial. When the number of awards won by rivals increases from zero to one, overconfident CEOs are associated with takeover probability increasing from 11.6% to 16.5%. On the other hand, we find no significant relation for the subsample excluding the overconfident CEOs. The results in Panel B using a 100% moneyness cutoff are quantitatively similar. The results in Table 8 therefore also appear to support the innovation peer pressure explanation, because overconfident CEOs tend to become more aggressive when they observe their peers' success. On the other hand, we would not expect to observe the influence of CEO overconfidence under the second mover's advantage explanation.

The third factor that could affect the impact of rivals' innovation award on acquisitiveness is corporate governance. Early papers such as Jensen (1986) suggest empire-building behavior of managers, especially through active acquisitions. Masulis, Wang, and Xie (2007) suggest that managers engage in empire-building acquisitions only when the corporate governance is not well executed. By the same token, R&D racing is not always value-enhancing because non-cooperated firms may over-invest in R&D in a Pareto sense (Mortensen, 1982) Therefore, ambitious managers who are not well governed could engage in innovation acquisitions when rivals' innovation awards are announced, no matter such takeover is value enhancing or not. We follow Gompers, Ishii, and Metrick's (2003) governance index (G-index) to measure the corporate governance of a firm. G-index is constructed by 24 corporate-governance provisions and proxies for the level of shareholder rights.[22] A firm with a low G-index is usually well governed and with strong shareholder rights.

We report logit regression results for subsamples sorted by governance, the G-index, in Table 9. We find that the coefficients of *log(1 + number of rivals' innovation awards)* are about 0.14 and are statistically significant at the 5% level or better. The coefficients are economically significant too. When the number of awards won by rivals increases from zero to one, firms with poor governance (high G-index) are associated with takeover probability increasing from 10.5% to 12.8%. On the other hand, there is no significant relation for the subsample of well-governed firms (low G-index). Similar to CEO overconfidence, managers and firms without sound corporate governance are more likely to engage in value-destroying actions, such as peer pressure -driven acquisitions. On the other hand, if acquisitions are driven by the second mover's advantage, we would expect no difference among two groups or even the opposite pattern.

The fourth conditional test we carry out is based on advertising expenditure. We have argued that the focal firm may adopt a stronger strategic response when its rivals' inventions are recognized by the media and thus well publicized. Media reports of R&D 100 Awards potentially lead to requests for managers to formulate an immediate response. Yet, if these very same rivals have spent heavily advertising their inventions to the consuming public, then the winning of an R&D 100 Award should be less unexpected to the focal firm. Thus, we expect that the impact of rivals' innovation awards on acquisitiveness is stronger for rivals without advertising expenditure if the acquisitiveness is related to attention (and surprise).

We report logit regression results for subsamples sorted by whether or not the rival firms spend on advertising in Table 10. We find that the coefficients of *log(1 + number of rivals' innovation awards)* in Models 1 and 2 are about 0.17 and are statistically significant at the 1% level. When the number of awards won by rivals that have *zero* advertising spending increases from zero to one, the takeover probability for rivals increases from 7.1% to 9.1%. On the other hand, there is no significant relation in the subsample of rivals with advertising spending (see

[22] G-index data and components are obtained from RiskMetrics Governance and Directors databases (formerly called IRRC, or Investor Responsibility Research Center).

Models 3 and 4).[23] Overall, Table 10 also appears to support the innovation peer pressure explanation that is closely related to managerial attention. On the other hand, the second mover's advantage does not have a clear prediction in the advertising-based subsample analysis.

5. The choice of targets

If firms are more acquisitive when their rivals win more innovation awards, then a natural question is to ask what type of targets do they bid on. First, we examine whether a target with higher Tobin's Q, smaller size, higher leverage, greater R&D intensity or with more patents is more attractive to potential bidders. Innovation-related variables are particularly of our interest. When a firm invents an award-winning technology, its peers that fall behind in the race could bid on R&D-intensive targets to play catch-up in technologies (as in the Cisco example at the beginning of this paper).

To test this proposition, we report target characteristics sorted by whether or not the rivals of the acquirer win innovation awards. As shown in Table 11, the mean and median R&D-to-assets ratio of target firms are 0.0947 and 0.0722 when the acquirers' rivals receive innovation awards. By the same token, the mean and median R&D-to-assets ratio of target firms are about 0.089 and 0.0281 when the acquirers' rivals *do not* win innovation awards. While the difference in means is small and insignificant, the difference in medians is large and significant at the 1% level. Moreover, the mean and median of patent counts of target firms are 0.9888 and 0.6931 in the award-winning innovation subgroup, and both those are statistically and economically higher than for target firms whose acquirers' rivals do not win innovation awards.

Next, we examine whether innovation award-motivated acquirers tend to bid for targets whose products overlap with their rivals. We use all M&A events between 1997 and 2014 for the logit regression analysis. The dependent variable is a dummy that equals one if a firm acquires a publicly traded target that is a two-digit SIC peer of its rivals that wins an award, and zero if the

[23] As an additional test, we split the whole sample into two subsamples by the median of analyst coverage, because rivals firms with more coverage attract more attention from the focal firm even absent innovation awards. Our (untabulated) results show that the impact of rivals' innovation awards on focal firms' acquisitions is significant only in the subsample of firms with below-median analyst coverage.

firm does not have a rival winning the award or bids other targets.[24] Thus, we are able to identify whether the target that is technologically overlapped with the acquirer's award-winning rivals is more appealing to the bidder.

Table 12 presents the results from the logit regression analysis. Models 1 and 2 use rivals' winning awards in the prior three years as the key independent variable while Models 3 and 4 use rivals' winning awards in the prior year as the main explanatory variable. The coefficients on *log(1 + number of rivals' innovation awards)* are all positive and statistically significant at the 1% level. These coefficient estimates are very economically substantial. When the number of award-winning products produced by rivals increases from zero to one, the focal firm's takeover probability of bidding for an overlapping target with its rivals increases from 0% to 32.5%. The results suggest again that the takeovers we observe appear to be triggered by rivals' winning awards, and further that the focal firm seems to confront their award-winning rivals by taking over targets related to these rivals in general.

6. Conclusion

Extant research has found that firms engage in acquisitions to gain access to technology from target firms, yet the underlying cause of innovation-driven acquisitions (instead of in-house R&D) remains underexplored. In this paper, we propose that the pressure from rivals' innovative activities, especially technology and product breakthroughs, is a primary motivation for these acquisitive firms. We gauge the pressure from rivals using the "R&D 100 Award", which is published by R&D Magazine (since 1965), and is often regarded as the "Oscar of Innovation." To identify a firm's rivals, we use the 10-K Text-based Network Industry Classifications (TNIC) data provided by Gerard Hoberg and Gordon Phillips (Hoberg and Phillips, 2010), and define a firm's competitors as the other ten firms with the highest similarity scores to the focal firm in a given year.

We find that the probability that a firm acquires a target increases significantly if its rivals have won innovation awards in the prior three years. When the number of award-winning

[24] Results are quantitatively similar if we use three-digit SIC peers of the acquirer's rivals in the logit regression analysis.

innovative products produced by rivals increases from zero to one, the firm's probability of engaging in an acquisition increases from 7.6% to 9.2%. We perform several robustness checks. First, we manually collect the lists of competitors (self) disclosed in the 10-K reports of all firms that win the award. Second, we define competitors as firms in the same three-digit SIC code. Both of tests offer results suggesting that firms are more acquisitive when their rivals receive a greater number of innovation awards. Third, we use the patents generated by rivals as an alternative measure of the innovativeness of the firm's competitors, and confirm that sample firms also become more acquisitive when their competitors announce more successful patents.

We are aware of two endogeneity issues: reverse causality and omitted variables. Rivals may increase their innovative activities to promote creative products that end up winning the R&D 100 Award if they are aware, particularly before a public announcement, that a rival is planning to acquire a target (reverse causality). Also, there may exist a factor that affects both acquisition propensity and innovation among a group of competitors (omitted variables, such as industry-level technological shocks). Therefore, we perform two-stage least square regression analysis using as an instrumental variable the state-level trade secret protection of competitors located in states different from the focal firm. We also construct a propensity score matched sample that is balanced in observable characteristics related to takeover propensity in an attempt to deal with potential omitted variables. We also use the list of finalists disclosed by R&D Magazine in 2015 to compare the differential effects of rivals winning awards and rivals being selected as a finalist. Our conclusion remains similar after considering these three endogeneity tests.

We propose three possible explanations for why the firm feels pressure when its rivals win innovation awards: an agency story and a second mover's advantage story from the acquirer's perspective, and a support-seeking explanation from the target's perspective. We perform announcement period abnormal return regression analyses for acquirers and acquisition regressions for targets to attempt to shed light on these three explanations. Our evidence suggests that an agency story based on innovation peer pressure could be more plausible.

In further tests of the channels which affect the impact of innovation peer pressure, we find that acquirers with greater industry concentration, more overconfident CEOs, poorer corporate governance, and rivals without advertisement expenditure appear to become more acquisitive following innovation awards won by rivals. These findings are intuitive and further support to an agency story based on innovation peer pressure.

Finally, we examine which types of targets are more likely to be acquired by firms under pressure from the publicized innovation achievements of their rivals. Our findings suggest that firms whose rivals win R&D 100 Awards tend to acquire more R&D-intensive targets and targets with more patents. Firms whose rivals have won awards also bid targets overlapped with the rivals in product markets. Two implications are suggested by these results. These acquisitions are designed to buy (rather than build) growth opportunities; that is, buying is certainly faster as a way of regaining technology parity with competitors.

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Appendix: A1

ID	Invention	Main contributor	Co-developers/Contributors
1	Acoustic Wavenumber Spectrometer (AWS)	Los Alamos National Laboratory	
2	Advanced Electrolyte Model (AEM)	Idaho National Laboratory	
3	Agilent Cary 7000 Univeral Measurement Spectrophotometer (UMS) and Universal Measurement Accessory	Agilent Technologies Australia (M) Pty Ltd	
4	Agilent Technologies N2820A Series High-Sensitivity, High Dynamic Range Current Probes	Agilent Technologies	
5	Airborne Sense and Avoid (ABSAA) Radar Panel	MIT Lincoln Laboratory	
6	Alcoa 951	Alcoa Inc.	
7	All-Fiber Isolator	AdValue Photonics	
8	Amended Silicates HgX	Novinda Corporation	
9	Argonne's Advanced Redox Shuttle Additive for Overcharge Protection of Lithium-Ion Batteries Used in Electric Vehicles	Argonne National Laboratory	
10	ASSIST Silver	Milliken & Company	Milliken Healthcare Products LLC
11	Automotive Phased Array Radar	Toyota Technical Center	Univ. of California, San Diego; Toyota Motor Corp.; Michigan Technological Research Institute; Fujitsu-Ten
12	BaDx	Sandia National Laboratories	Univ. of New Mexico
13	Beam Instruments	Brookhaven National Laboratory	Korea Univ.
14	Berkeley Lab Multiplex Chemotyping Microarray	Lawrence Berkeley National Laboratory	
15	BETAMATE 1630 Structural Adhesive	Dow Europe GmbH	The Dow Chemical Company; Dow Automotive Systems
16	BioSig3D	Lawrence Berkeley National Laboratory	
17	bq25570 nanopower boost charger with integrater buck	Texas Instruments	
18	Clarisolve	EMD Millipore	
19	Continuously Variable Series Reactor (CVSR)	Oak Ridge National Laboratory	SPX Transformer Solutions Inc.; University of Tennessee
20	Convergent Polishing: Rapid, Simple, Low Cost Finishing of High Quality Glass Optics	Lawrence Livermore National Laboratory	
21	CORTECS Columns	Waters Corporation	

22	Dedicated-EGR (D-EGR)	Southwest Research Institute (SwRI)	
23	Diagnosis Using the Choas of Computing Systems (DUCCS)	Oak Ridge National Laboratory	
24	Direct Gas to Wafer Epitaxial System	Crystal Solar Inc.	National Renewable Energy Laboratory
25	EcoTuff	United Technologies Research Center (UTRC)	Pratt & Whitney; 3M Corp.
26	ELYRA P.1 with 3D PALM	Carl Zeiss Microscopy LLC	
27	eXact iDip photometer	Industrial Test Systems Inc.	
28	Extreme-power Ultra-low-loss Dispersive Element (EXUDE)	Lawrence Livermore National Laboratory	Lockheed Martin Laser and Sensor Systems Advanced Thin Films
29	Flexure-based Electromagnetic Linear Actuator	Singapore Institute of Manufacturing Technology	
30	Foldscope	Stanford Univ.	
31	Genuity DroughtGard Hybrids	Monsanto	
32	Glyph	Pacific Northwest National Laboratory	Avegant Corporation
33	GOMA 6.0	Sandia National Laboratories	Gillette/P&G; Drexel Univ.; Google; 3M Corporate Research Process Lab; Univ. of New Mexico; Prism Software
34	Haystack Ultrawideband Satellite Imaging Radar (HUSIR)	MIT Lincoln Laboratory	Simpson Gumpertz and Heger Inc.; Communications & Power Industries
35	HECLOT: High-efficiency calcium looping technology	Industrial Technology Research Institute (ITRI)	
36	High-Capacitance Radio-Frequency Curled Microelectromechanical Switch (CMEMS)	MIT Lincoln Laboratory	Innovative Micro Technology
37	High-Performance Silicon Carbide-based Plug-In Hybrid Electric Vehicle Battery Charger	Arkansas Power Electronics International Inc. (APEI)	Oak Ridge National Laboratory; Univ. of Arkansas; Toyota Research Institute of North America; Cree Inc.; Advanced Research Projects Agency - Energy
38	Hitachi Cs-Sr simultaneous adsorbent	Hitachi Research Laboratory, Hitachi Ltd	Hitachi-GE Nuclear Energy Ltd.
39	HP Apollo Platform for High-Performance Computing	National Renewable Energy Laboratory	Hewlett-Packard Company
40	Hysitron Biomechanical Test Instrument	Hysitron Inc.	
41	IA3100 HPIMS HPLC Detector	Excellims Corporation	
42	ICTA: In-Line Compact Thermal Analyzer	Industrial Technology Research Institute (ITRI)	
43	Intellipigment	Univ. of Central Florida	HySense Technology LLC; NASA John F. Kennedy Space Center
44	Ionic liquid anti-wear additives for fuel-efficient engine lubricants	Oak Ridge National Laboratory	General Motors Research and Development Center; Shell Global Solutions (US); Lubrizol Corporation
45	iQ Series Comfort Knit/Amplitude G2 Flame	Milliken & Company	Bulwark FR

	Resistant Fabric		
46	iSPM: Intelligent Software Suite for Personalized Modeling of Expert Opinions, Decisions, and Errors in Visual Examination Tasks	Oak Ridge National Laboratory	
47	ITOS PHASER 3000 Light Module	OSRAM GmbH	OSRAM SYLVANIA T.Q. Technology Co. Ltd.
48	JFE-TF1	JFE Steel Corporation	
49	LDC1000 Inductance-to-Digital Converter	Texas Instruments	
50	Leica TCS SP8 STED 3X	Leica Microsystems CMS GmbH	Max Planck Institute for Biophysical Chemistry
51	Li-Foil Neutron Detectors	Kansas State Univ., SMART Laboratory	Saint-Gobain Crystals
52	Liberty Blue Automated Microwave Peptide Synthesizer	CEM Corp.	
53	Localizing Ground Penetrating Radar (LGPR)	MIT Lincoln Laboratory	
54	LumiMap	Bruker Nano Surfaces	
55	Lunar Laser Communication System (LLCS)	MIT Lincoln Laboratory	NASA Goddard Space Flight Center
56	MELFA-3D Vision	Mitsubishi Electric Corporation	
57	Micro GC Fusion	INFICON	
58	microTLC	Lawrence Livermore National Laboratory	Field Forensics Inc.
59	Multiphysics Object Oriented Simulation Environment (MOOSE)	Idaho National Laboratory	
60	NanoFab Lab...in a Box!	Argonne National Laboratory	EChem Nanowires Educational Foundation Inc.
61	NANOSLIDE	Daimler AG	Gebr. Heller Maschinenfabrik GmbH
62	neoClose	neoSurgical	
63	NEPTUNE subsea insulation system	The Dow Chemical Company	Dow Infrastructure Comfort Energy Efficiency; Dow Oil, Gas and Mining
64	NinePoint Medical NvisionVLE Imaging System	NinePoint Medical	Farm Design Inc.
65	Noviplex Plasma Collection Card	Novilytic	
66	Passive Vaccine Storage Devices	Stratos Product Development	Intellectual Ventures Labs/Global Good
67	Plasmon-Excitation Optical Scanning Probe Microscope (Optical SPM)	Yokohama Research Laboratory, Hitachi Ltd	
68	Portable Aluminum Deposition System (PADS)	Oak Ridge National Laboratory	United Technologies Research Center (UTRC); Univ. of Mississippi
69	Preferred RCS Garnet 2.0 resin coated sand utilizing Dow's TERAFORCE technology	The Dow Chemical Company	Preferred Sands; Dow Polyurethanes
70	PTT DIESEL CNG	PTT Public Company Ltd	
71	RF-DPF Diesel Particulate Filter Sensor	Filter Sensing Technologies Inc.	

72	SAFIRE	Los Alamos National Laboratory	Chevron ETC; GE Measurement & Control
73	SALVI: System for Analysis at the Liquid Vacuum Interface	Pacific Northwest National Laboratory	
74	Sensor-less Servo Drive Unit FRE700EX Series & Sensor-less Motor MM-GKR	Mitsubishi Electric Corporation	
75	SIRTURO (bedaquiline)	Janssen Research & Development LLC	
76	SIS Lithography	Argonne National Laboratory	
77	SmartFlare RNA Detection Probes	EMD Millipore	
78	Solar Thermochemical Advanced Reactor System (STARS)	Pacific Northwest National Laboratory	DiverSolar LLC
79	Solid Polymer Ionic Liquid (SPIL) Rechargeable Lithium Battery	SolidEnergy Systems	
80	Stripe CDG	INFICON	
81	Super-hydro-tunable HiPAS membranes	Oak Ridge National Laboratory	
82	Superconducting Tunnel Junction X-Ray Spectrometer	Lawrence Livermore National Laboratory	STAR Cryoelectronics LLC
83	Superelastic Intermetallic Nickel Titanium Alloys and Manufacturing Techniques for Advanced Bearing Applications	NASA Glenn Research Center	Abbott Ball Company
84	syngo.CT Bone Reading	Siemens Corporation	Siemens AG H IM CR
85	TEQUATIC PLUS Fine Particle Filter	Clean Filtration Technologies LLC, a Dow Chemical Company	The Dow Chemical Company
86	The ChemStik Technology	Green Theme Technologies LLC	Under Armour Inc.
87	The SaTo Hygienic Toilet Pan	American Standard	
88	Therma-Base	NASA Glenn Research Center	Thermacore Inc.
89	Thermo Scientific Delta Ray Isotope Ratio Infrared Spectrometer	Thermo Fisher Scientific	
90	Thermo Scientific Dionex ERS 500 Electrolytically Regenerated Suppressor	Thermo Fisher Scientific	
91	Thermo Scientific RIIDEyeX	Thermo Fisher Scientific	
92	Tissue-Specific Cell-Wall Engineering for Biofuels and Biomaterials	Lawrence Berkeley National Laboratory	
93	Transform WG Insecticide and Closer SC Insecticide with Isoclast Active	Dow AgroSciences LLC	
94	Triplet-Harvesting Plastic Scintillators (THPS)	Sandia National Laboratories	Radiation Monitoring Devices Inc.; Univ. of California, Riverside
95	TruTag Product Authentication Solution	TruTag Technologies Inc.	

96	Vertisense Scanning Thermal Microscopy Module	Applied NanoStructures Inc. (AppNano)	
97	VR-3000 Series One-shot 3-D Measurement Macroscope	KEYENCE Corp.	
98	Wide-Area Chemical Sensor (WACS)	MIT Lincoln Laboratory	
99	XPE205 Excellence Analytical Laboratory Balance	Mettler Toledo	
100	xSol	Hysitron Inc.	

Appendix: A2

Sorted by one-digit SIC		Frequency
0	Agriculture, Forestry, And Fishing	
1	Mining and Construction	2.25%
2	Manufacturing- Food, chemicals and allied products, petroleum refining and so on	15.34%
3	Manufacturing- Plastics products, primary metal, computer equipment, electronic equipment, measuring and controlling instruments and so on	71.03%
4	Transportation, Communications, Electric, Gas, And Sanitary Services	5.69%
5	Wholesale Trade	0.40%
7	Services- Hotel, business services, automotive repair and so on	1.98%
8	Services- Health services, educational services, and so on	3.04%
9	Public Administration	0.26%
Sorted by two-digit SIC		
28	Biotech and pharmaceuticals	12.17%
35	Computers and machinery	9.26%
36	Electrical and electronics	16.14%
37	Transportation equipment	12.43%
38	Medical and scientific instruments	23.81%
Others	Others	26.19%

Appendix: A3

# of innovation awards that a firm wins	Percentage
1	62.93%
2	14.63%
3	5.78%
4	3.06%
5	1.36%
6	0.68%
7	1.02%
8	0.68%
9	0.68%
10	0.68%
11	0.68%
12	1.70%
14	0.68%
16	0.68%
17	0.68%
18	0.68%
22	0.34%
23	0.68%
26	0.34%
33	0.34%
42	0.34%
44	0.34%
62	0.68%
131	0.34%

Appendix: A4

Variable	Definition
M&A indicator	Indicator variable equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise.
Number of rivals' innovation awards	The number of rivals' innovation awards between year t-2 and t (or in year t for some panels), rivals are the ten firms with the highest Hoberg and Phillips (2010) pairwise similarity scores.
Number of own-firm innovation awards	The number of innovation awards won by the firm between year t and t-2
Tobin's Q	The market value of common equity plus total assets and minus book value of common equity, scaled by book assets, measured by year t.
PPE	The total value of property, plant and equipment scaled by total assets, measured at year t.
Cash ratio	Cash and short-term investment scaled by total assets, measured at year t.
Size	The market value of common equity, measured at year t.
Leverage	Total debt scaled by total assets, measured at year t.
ROA	Earnings before interest, taxes, depreciation, and amortization scaled by total assets, measured at year t.
Sales growth	The growth rate of sales, measured at year t.
R&D to assets	Research and development expenses scaled by total assets, measured at year t.
Patent count	Number of patents that are filed by a firm in year t and are granted later (successful patent application).
Industry M&A indicator	Indicator variable equal to one if at least one takeover occurred in the same three-digit SIC industry in year t; zero otherwise.
HHI	Herfindahl index, which is the sum of squared market shares (firm sales-to-industry sales ratio) in a three-digit SIC industry, measured at year t.
Industry sales growth	Industry-level sales growth rate of a three-digit SIC industry, measured at year t.
Industry patent count	The sum of patent counts of all firms in a three-digit SIC industry in year t.
CEO overconfidence	A CEO is identified as an overconfident CEO if s/he retains exercisable stock options that are more than 67% (or 100%) in the money.
G-index	Gompers, Ishii, and Metrick's (2003) G-index. G-index data and components are obtained from RiskMetrics Governance and Directors databases (formerly called IRRC, or Investor Responsibility Research Center).
Advertising spending	Advertising expense reported in the Compustat database, which represents the cost of advertising media (radio, television, newspapers, periodicals) and promotional expenses.

Appendix: A5

	Acquisition activity in 2016		Total
	No	Yes	
The own-firm whose rivals are in final list and win R&D 100 Award in 2015	26 83.87%	5 16.13%	31
The own-firm whose rivals are in final list but do not win R&D 100 Award in 2015	17 94.44%	1 5.56%	18

Table 1: Summary Statistics

This table reports summary statistics for our sample of U.S. firms between 1996 and 2013. Definitions of the variables are provided in Table A4 in the Appendix.

Variable	Mean	Std Dev	10th Pctl	Lower Quartile	Median	Upper Quartile	90th Pctl
Number of rivals' innovation awards in one year	0.0786	0.5530	0.0000	0.0000	0.0000	0.0000	0.0000
Number of rivals' innovation awards in three years	0.2379	1.5050	0.0000	0.0000	0.0000	0.0000	0.0000
Number of own-firm innovation awards	0.0212	0.3652	0.0000	0.0000	0.0000	0.0000	0.0000
Tobin's Q	2.6406	11.3497	0.8815	1.0926	1.5156	2.4551	4.3286
PPE	0.2589	0.2323	0.0343	0.0767	0.1793	0.3778	0.6415
Cash ratio	0.2085	0.2348	0.0082	0.0283	0.1103	0.3174	0.5874
Size (mil)	2,823	14,931	17	57	254	1,088	4,147
Leverage	0.3497	1.9372	0.0000	0.0178	0.2444	0.4896	0.7071
ROA	0.0411	0.3308	-0.2057	0.0202	0.1035	0.1632	0.2288
Sales growth	0.9497	61.2084	-0.1796	-0.0226	0.0881	0.2560	0.6132
R&D to assets	0.0639	0.1913	0.0000	0.0000	0.0010	0.0701	0.1818
Patent count	9.7733	94.9511	0.0000	0.0000	0.0000	1.0000	8.0000
Industry M&A indicator	0.7697	0.4210	0.0000	1.0000	1.0000	1.0000	1.0000
HHI	0.2303	0.2128	0.0588	0.0851	0.1601	0.2889	0.4976
Industry sales growth	0.1471	16.6564	-0.1219	-0.0037	0.0670	0.1239	0.2266
Industry patent count	121.7317	716.8433	0.0000	0.0000	0.0000	11.0000	128.0000
M&A indicator	0.0816	0.2738	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2: Logit Regression Analysis of Being an Acquirer

This table reports coefficient estimates from logit regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is M&A indicator, which is equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise. In this table, we compute the number of rivals' innovation awards as follows. We define a firm's rivals as the ten firms with the highest similarity scores to the focal firm in a given year using the 10-K Text-based Network Industry Classifications (TNIC) data from Hoberg and Phillips (2010). We then measure the number of R&D 100 awards won by these rivals in the prior three years or one year. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

	Looking at rivals' innovation awards in past three years		Looking at rivals' innovation awards in past one year	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.1016**	0.1021**	0.1546**	0.1565**
	(0.018)	(0.018)	(0.024)	(0.021)
Log(1 + number of own-firm innovation awards)	0.0242	0.0462	0.0300	0.0517
	(0.815)	(0.656)	(0.774)	(0.622)
Tobin's Q	0.0164***	0.0172***	0.0163***	0.0170***
	(0.005)	(0.004)	(0.005)	(0.005)
PPE	-0.9174***	-0.9235***	-0.9174***	-0.9234***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash ratio	0.0447	-0.0184	0.0422	-0.0209
	(0.622)	(0.841)	(0.641)	(0.819)
Log(size)	0.2588***	0.2576***	0.2591***	0.2579***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.2033***	-0.2003***	-0.2032***	-0.2003***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.1602*	0.1573*	0.1596*	0.1566*
	(0.073)	(0.078)	(0.075)	(0.080)
Sales growth	-0.0004	-0.0005	-0.0004	-0.0005
	(0.249)	(0.258)	(0.249)	(0.259)
R&D to assets	-0.5231**	-0.6665***	-0.5258**	-0.6700***
	(0.015)	(0.007)	(0.015)	(0.007)
Log(1 + patent count)	0.0489***	0.0386***	0.0497***	0.0394***
	(0.000)	(0.005)	(0.000)	(0.004)
Industry M&A indicator		0.3328***		0.3327***
		(0.000)		(0.000)
HHI		-0.0993		-0.0986
		(0.408)		(0.411)
Industry sales growth		0.0053		0.0055
		(0.881)		(0.875)
Log(1 + industry patent count)		0.0386***		0.0387***
		(0.000)		(0.000)
Intercept	-6.8241***	-7.0309***	-6.8251***	-7.0325***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	61,157	61,157	61,157	61,157
-2 Log Likelihood	38,481	33,510	33,510	33,510

Table 3: Two Stage Least Squares Regression Analysis

This table reports coefficient estimates from two stage least squares regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. In the first stage, we regress log(number of rivals' innovation awards) on the state-level average headquarter-state UTSA variables for rivals from states different than the focal firms, and other control variables. UTSA is a score measuring the strength of trade secret laws for each state. Common law is a score measuring the strength of common law precedent and enforcement at the state level. In the second stage, the dependent variable is M&A indicator, which is equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise. Definitions of other variables are contained in the Appendix Table A4. Regression models include year and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

Panel A: Rivals' innovation awards in past three years

	Model 1		Model 2		Model 3		Model 4	
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
Average UTSA	0.3193***		0.3127***					
	(0.000)		(0.000)					
Average UTSA plus common law score					0.2759***		0.2649***	
					(0.000)		(0.000)	
Log(1 + number of rivals' innovation awards)^		2.0628***		2.1062***		2.4950***		2.5992***
		(0.003)		(0.003)		(0.000)		(0.000)
Log(1 + number of own-firm innovation awards)		-0.0936	0.2376***	-0.5941***		-0.0917	0.2391***	-0.7131***
		(0.525)	(0.000)	(0.009)		(0.533)	(0.000)	(0.002)
Tobin's Q	-0.0030***	0.0227***	-0.0017***	0.0203***	-0.0029***	0.0243***	-0.0017***	0.0215***
	(0.003)	(0.002)	(0.005)	(0.005)	(0.003)	(0.001)	(0.006)	(0.003)
PPE	-0.0159	-1.1871***	-0.0167	-1.1847***	-0.0136	-1.1880***	-0.0140	-1.1856***
	(0.234)	(0.000)	(0.199)	(0.000)	(0.307)	(0.000)	(0.280)	(0.000)
Cash ratio	-0.0910***	0.2092	-0.0839***	0.1981	-0.1004***	0.2496*	-0.0918***	0.2376
	(0.000)	(0.159)	(0.000)	(0.178)	(0.000)	(0.098)	(0.000)	(0.111)
Log(size)	0.0186***	0.2235***	0.0052***	0.2509***	0.0184***	0.2152***	0.0052***	0.2474***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.0009	-0.1197*	0.0007	-0.1194*	0.0009	-0.1144*	0.0008	-0.1142*
	(0.223)	(0.056)	(0.285)	(0.057)	(0.201)	(0.057)	(0.261)	(0.058)
ROA	-0.0100**	0.1649	-0.0094**	0.1641	-0.0083*	0.1630	-0.0097**	0.1673
	(0.050)	(0.123)	(0.046)	(0.125)	(0.098)	(0.124)	(0.042)	(0.115)
Sales growth	0.0001**	-0.0002	0.0001***	-0.0002	0.0000*	-0.0002	0.0001***	-0.0002
	(0.051)	(0.442)	(0.003)	(0.446)	(0.065)	(0.445)	(0.004)	(0.450)
R&D to assets		-0.9963***	-0.0556***	-0.8792***		-1.0660***	-0.0632***	-0.9018***
		(0.003)	(0.000)	(0.010)		(0.002)	(0.000)	(0.010)
Log(1 + patent count)		0.0430*	0.0507***	-0.0637		0.0411*	0.0498***	-0.0884**
		(0.066)	(0.000)	(0.129)		(0.078)	(0.000)	(0.030)
Industry M&A indicator	0.0015	0.3055***	0.0037	0.3010***	0.0017	0.3046***	0.0038	0.2989***
	(0.821)	(0.003)	(0.569)	(0.003)	(0.799)	(0.003)	(0.550)	(0.003)
HHI	0.0675***	-0.1640	0.0371***	-0.1029	0.0699***	-0.1847	0.0394***	-0.1127
	(0.000)	(0.332)	(0.002)	(0.536)	(0.000)	(0.273)	(0.001)	(0.497)
Industry sales growth	-0.0010	0.0203	-0.0003	0.0187	-0.0011	0.0207	-0.0003	0.0189
	(0.823)	(0.622)	(0.947)	(0.649)	(0.819)	(0.614)	(0.935)	(0.645)
Log(1 + industry patent count)	0.0019	0.0300**	-0.0026	0.0396***	0.0013	0.0294**	-0.0031*	0.0407***
	(0.249)	(0.024)	(0.114)	(0.003)	(0.451)	(0.027)	(0.065)	(0.002)
Intercept	-0.2267***	-6.3444***	-0.0553***	-6.6978***	-0.2265***	-6.2578***	-0.0573***	-6.6749***
	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	61,157	61,157	61,157	61,157	61,157	61,157	61,157	61,157
Adj Rsq	0.0920		0.1190		0.0928		0.1192	
-2 Log Likelihood		15,738		15,738		15,738		15,738

Panel B: Rivals' innovation awards in past one year								
	Model 1		Model 2		Model 3		Model 4	
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
Average UTSA	0.1471***		0.1436***					
	(0.000)		(0.000)					
Average UTSA plus common law score					0.1285***		0.1226***	
					(0.000)		(0.000)	
Log(1 + number of rivals' innovation awards)^		4.4774***		4.5855***		5.3573***		5.6133***
		(0.003)		(0.003)		(0.000)		(0.000)
Log(1 + number of own-firm innovation awards)		-0.0936	0.1149***	-0.6204		-0.0917	0.1155***	-0.7402***
		(0.525)	(0.000)	(0.008)		(0.533)	(0.000)	(0.001)
Tobin's Q	-0.0012***	0.0219***	-0.0006**	0.0193***	-0.0012***	0.0232***	-0.0006**	0.0202***
	(0.008)	(0.003)	(0.029)	(0.007)	(0.009)	(0.002)	(0.032)	(0.005)
PPE	-0.0088	-1.1804***	-0.0094	-1.1770***	-0.0078	-1.1800***	-0.0082	-1.1761***
	(0.255)	(0.000)	(0.219)	(0.000)	(0.309)	(0.000)	(0.280)	(0.000)
Cash ratio	-0.0449***	0.2223	-0.0422***	0.2150	-0.0493***	0.2631*	-0.0459***	0.2566*
	(0.000)	(0.139)	(0.000)	(0.150)	(0.000)	(0.084)	(0.000)	(0.090)
Log(size)	0.0086***	0.2235***	0.0019***	0.2531***	0.0085***	0.2157***	0.0019***	0.2503***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
Leverage	0.0000	-0.1181*	0.0000	-0.1178*	0.0001	-0.1125*	0.0000	-0.1122*
	(0.739)	(0.059)	(0.828)	(0.060)	(0.640)	(0.062)	(0.985)	(0.062)
ROA	-0.0041	0.1626	-0.0023	0.1546	-0.0033	0.1600	-0.0024	0.1555
	(0.114)	(0.128)	(0.365)	(0.148)	(0.197)	(0.131)	(0.348)	(0.142)
Sales growth	0.0001**	-0.0002	0.0001***	-0.0002	0.0000*	-0.0002	0.0001***	-0.0002
	(0.041)	(0.435)	(0.001)	(0.440)	(0.054)	(0.436)	(0.001)	(0.442)
R&D to assets		-0.9963***	-0.0204***	-0.9027***		-1.0660***	-0.0240***	-0.9315***
		(0.003)	(0.001)	(0.008)		(0.002)	(0.000)	(0.007)
Log(1 + patent count)		0.0430*	0.0253***	-0.0731		0.0411*	0.0249***	-0.0988**
		(0.066)	(0.000)	(0.101)		(0.078)	(0.000)	(0.021)
Industry M&A indicator	0.0034	0.2933***	0.0045	0.2881***	0.0035	0.2901***	0.0046	0.2833***
	(0.347)	(0.004)	(0.207)	(0.005)	(0.336)	(0.004)	(0.199)	(0.005)
HHI	0.0347***	-0.1801	0.0197***	-0.1151	0.0359***	-0.2026	0.0208***	-0.1271
	(0.000)	(0.290)	(0.010)	(0.490)	(0.000)	(0.232)	(0.007)	(0.445)
Industry sales growth	-0.0029	0.0313	-0.0025	0.0298	-0.0030	0.0339	-0.0026	0.0325
	(0.300)	(0.447)	(0.309)	(0.469)	(0.303)	(0.410)	(0.308)	(0.430)
Log(1 + industry patent count)	0.0004	0.0321**	-0.0019***	0.0427***	0.0001	0.0319***	-0.0021***	0.0445***
	(0.613)	(0.016)	(0.021)	(0.002)	(0.888)	(0.016)	(0.010)	(0.001)
Intercept	-0.1036***	-6.3268***	-0.0183	-6.7088***	-0.1035***	-6.2431***	-0.0193	-6.6897***
	(0.000)	(0.000)	(0.130)	(0.000)	(0.000)	(0.000)	(0.111)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	61,157	61,157	61,157	61,157	61,157	61,157	61,157	61,157
Adj Rsq	0.0946		0.08284		0.06507		0.08307	
-2 Log Likelihood		15,738		15,738		15,738		15,738

Table 4: Logit Regression Analysis of Being an Acquirer - Propensity Score Matching

This table reports coefficient estimates from logit regressions with matched samples. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is M&A indicator, which is equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise. We use two propensity-score-matched samples. Propensity matched sample (A) is constructed as follows. For each M&A acquirer at year t+1, we find all firms in the same year and industry (two-digit SIC code) that were not acquirers in the three-year period prior, and then filter these matches by calculating propensity scores estimated using size and the ratio of book equity to market equity in year t. We find up five matched firms for each M&A acquirer. Propensity matched sample (B) is constructed similarly, except we calculate propensity scores using size, the ratio of book equity to market equity, sales growth, patent count, and ROA in year t. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

Panel A: Rivals' innovation awards in past three years

	Propensity matched sample (A)		Propensity matched sample (B)	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.1193***	0.1147***	0.1300***	0.1268***
	(0.009)	(0.012)	(0.004)	(0.005)
Log(1 + number of own-firm innovation awards)	0.2054*	0.2412**	0.1988*	0.2312**
	(0.091)	(0.045)	(0.094)	(0.049)
Tobin's Q	0.0069	0.0073	0.0084	0.0091
	(0.304)	(0.283)	(0.228)	(0.195)
PPE	-1.3330***	-1.3231***	-1.3431***	-1.3327***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash ratio	-0.2739***	-0.3571***	-0.2947***	-0.3785***
	(0.006)	(0.000)	(0.003)	(0.000)
Log(size)	0.2717***	0.2709***	0.2901***	0.2896***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.2383***	-0.2339***	-0.2311***	-0.2269***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.0832	0.0779	0.0594	0.0459
	(0.302)	(0.343)	(0.562)	(0.661)
Sales growth	-0.0008*	-0.0009*	-0.0006	-0.0007
	(0.070)	(0.059)	(0.320)	(0.261)
R&D to assets	-0.3439	-0.5196*	-0.3305	-0.5170*
	(0.144)	(0.059)	(0.155)	(0.064)
Log(1 + patent count)	0.0832***	0.0710***	0.0733***	0.0600***
	(0.000)	(0.000)	(0.000)	(0.000)
Industry M&A indicator		0.6526***		0.6577***
		(0.000)		(0.000)
HHI		0.1223		0.1814
		(0.371)		(0.175)
Industry sales growth		0.0484		0.0637
		(0.444)		(0.289)
Log(1 + industry patent count)		0.0503***		0.0538***
		(0.000)		(0.000)
Intercept	-4.2377***	-4.8087***	-4.6254***	-5.2345***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	35,003	35,003	35,003	35,003
-2 Log Likelihood	25,362	25,362	26,336	26,336

Panel B: Rivals' innovation awards in past one year				
	Propensity matched sample (A)		Propensity matched sample (B)	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.2094*** (0.006)	0.2015*** (0.007)	0.2221*** (0.003)	0.2162*** (0.003)
Log(1 + number of own-firm innovation awards)	0.2116* (0.085)	0.2469** (0.043)	0.2041* (0.088)	0.2360** (0.047)
Tobin's Q	0.0068 (0.314)	0.0072 (0.291)	0.0083 (0.237)	0.0089 (0.203)
PPE	-1.3321*** (0.000)	-1.3222*** (0.000)	-1.3427*** (0.000)	-1.3321*** (0.000)
Cash ratio	-0.2756*** (0.006)	-0.3589*** (0.000)	-0.2972*** (0.003)	-0.3812*** (0.000)
Log(size)	0.2719*** (0.000)	0.2711*** (0.000)	0.2904*** (0.000)	0.2899*** (0.000)
Leverage	-0.2381*** (0.000)	-0.2338*** (0.000)	-0.2307*** (0.000)	-0.2266*** (0.000)
ROA	0.0826 (0.306)	0.0773 (0.347)	0.0585 (0.568)	0.0449 (0.668)
Sales growth	-0.0008* (0.070)	-0.0009* (0.059)	-0.0006 (0.318)	-0.0008 (0.259)
R&D to assets	-0.3470 (0.142)	-0.5228* (0.058)	-0.3339 (0.152)	-0.5210* (0.062)
Log(1 + patent count)	0.0840*** (0.000)	0.0718*** (0.000)	0.0743*** (0.000)	0.0610*** (0.000)
Industry M&A indicator		0.6520*** (0.000)		0.6570*** (0.000)
HHI		0.1234 (0.366)		0.1829 (0.171)
Industry sales growth		0.0487 (0.441)		0.0639 (0.287)
Log(1 + industry patent count)		0.0504*** (0.000)		0.0540*** (0.000)
Intercept	-4.2383*** (0.000)	-4.8096*** (0.000)	-4.6261*** (0.000)	-5.2358*** (0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	35,003	35,003	35,003	35,003
-2 Log Likelihood	25,363	25,363	26,336	26,336

Table 5: Regression Analysis of M&A Announcement Returns for Acquirers

This table reports coefficient estimates from regressions for M&A announcement abnormal returns for acquirers. The sample contains M&A announcement events between 1997 and 2014. M&A announcement abnormal return is computed as the 5-day (-2, 2) announcement return subtracting fitted return from Capital Asset Pricing Model. G-index is Gompers, Ishii, and Metrick's (2003) G-index. All cash indicator (all stock indicator) is equal to one if the method of payment for the M&A deal is all cash (all stock swap). Private target indicator is equal to one if the target is a private firm. Tender offer indicator is equal to one if the M&A is a tender offer deal. Relative deal size is the fraction of the size of acquirers to the size of targets. Stock run-up is the 200-day window stock return from event day -210 to -11. Free cash flow is the earnings before interest, tax and depreciation subtracting capital expenditure, and then scaled by book asset. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are t-values. ***, **, or * represent 1%, 5%, or 10% significance levels.

	Model 1	Model 2	Model 3
Log(1 + number of rivals' innovation	-0.0050**	-0.0051**	-0.0047**
awards)	(-2.178)	(-2.164)	(-2.299)
Log(1 + number of own-firm innovation	0.0184	0.0192*	0.0089
awards)	(1.606)	(1.672)	(1.335)
R&D to assets	-0.0054	-0.003	-0.0604
	(-0.146)	(-0.077)	(-1.607)
Log(1 + patent count)	0.0021	0.0023	0.0031**
	(1.451)	(1.519)	(2.52)
G-index			-0.0014**
			(-1.988)
All cash indicator	-0.0004	0.000	0.0047
	(-0.06)	(0.002)	(0.758)
All stock indicator	-0.0175**	-0.018**	-0.0123
	(-2.041)	(-2.08)	(-1.509)
Private target indicator	-0.0032	-0.0031	-0.0033
	(-0.881)	(-0.851)	(-0.921)
Tender offer indicator	-0.0074	-0.0075	-0.0111*
	(-1.191)	(-1.213)	(-1.908)
Relative deal size	-0.0001	-0.0001	0.0025
	(-0.153)	(-0.149)	(0.658)
Log(firm age)	0.0028	0.0028	0.0034
	(1.583)	(1.615)	(1.496)
Stock run-up	0.0231***	0.0232***	0.023***
	(4.762)	(4.783)	(4.217)
Log(size)	-0.0077***	-0.0076***	-0.0061***
	(-6.019)	(-5.867)	(-4.798)
Free cash flow	-0.0156	-0.0142	-0.0047
	(-0.946)	(-0.86)	(-0.184)
Leverage	0.0025	0.0023	-0.0005
	(0.553)	(0.488)	(-0.114)
Industry MA Indicator		-0.0081	-0.005
		(-1.556)	(-0.942)
HHI		-0.0049	0.0053
		(-0.552)	(0.612)
Industry sales growth		-0.0136*	-0.0064
		(-1.851)	(-1.322)
Log(1 + industry patent count)		-0.0004	-0.0014
		(-0.485)	(-1.547)
Intercept	0.1148***	0.1234***	0.1093***
	(6.159)	(6.308)	(5.501)
2-digit SIC industry indicators	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes
N	3695	3695	2279
Adjusted R-square	-0.001	0.000	-0.017

Table 6: Logit Regression Analysis of Being a Target

This table reports coefficient estimates from logit regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is M&A indicator, which is equal to one if a firm is targeted in a successful or unsuccessful M&A transaction in year t+1; zero otherwise. In this table, we compute the number of rivals' innovation awards as follows. We define a firm's rivals as the ten firms with the highest similarity scores to the focal firm in a given year using the 10-K Text-based Network Industry Classifications (TNIC) data from Hoberg and Phillips (2010). We then measure the number of R&D 100 awards won by these rivals in the prior three years or one year. Blockholder indicator is equal to one if a firm has at least an institutional investor with more than 5% ownership. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

	Rivals' innovation awards in past three years		Rivals' innovation awards in past year	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	-0.0425	-0.0409	0.0173	0.0210
	(0.541)	(0.555)	(0.871)	(0.844)
Log(1 + number of own-firm innovation awards)	0.3009	0.3292	0.2847	0.3127
	(0.191)	(0.156)	(0.214)	(0.177)
Tobin's Q	-0.0733***	-0.0736***	-0.0730***	-0.0732***
	(0.001)	(0.001)	(0.001)	(0.001)
PPE	-0.3141**	-0.3064**	-0.3125**	-0.3049**
	(0.024)	(0.031)	(0.025)	(0.032)
Cash ratio	0.4189***	0.3135**	0.4235***	0.3181**
	(0.001)	(0.017)	(0.001)	(0.015)
Log(size)	-0.0974***	-0.0967***	-0.0979***	-0.0972***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.0641	-0.0616	-0.0640	-0.0615
	(0.240)	(0.250)	(0.241)	(0.251)
ROA	0.1176	0.1013	0.1180	0.1017
	(0.263)	(0.327)	(0.261)	(0.325)
Sales growth	-0.0039	-0.0038	-0.0038	-0.0038
	(0.296)	(0.298)	(0.296)	(0.299)
R&D to assets	0.4520***	0.3846**	0.4533***	0.3858**
	(0.004)	(0.015)	(0.004)	(0.015)
Log(1 + patent count)	-0.1694***	-0.1852***	-0.1710***	-0.1867***
	(0.000)	(0.000)	(0.000)	(0.000)
Blockholder indicator	0.7577***	0.7629***	0.7574***	0.7626***
	(0.000)	(0.000)	(0.000)	(0.000)
Industry M&A indicator		0.0624		0.0625
		(0.394)		(0.393)
HHI		-0.2186		-0.2212
		(0.168)		(0.163)
Industry sales growth		-0.0196		-0.0197
		(0.771)		(0.769)
Log(1 + industry patent count)		0.0546***		0.0545***
		(0.000)		(0.000)
Intercept	-3.7078***	-3.7112***	-3.7053***	-3.7071***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	68,057	68,057	68,057	68,057
-2 Log Likelihood	21,621	21,621	21,621	21,621

Table 7: Logit Regression Analysis of Being an Acquirer - Industry Concentration

This table reports coefficient estimates from logit regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is M&A indicator, which is equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise. In Panel A, we sort the sample by the HHI index (three-digit SIC industry) of the acquirer. In Panel B, we identify the top ten rivals based on pairwise similarity from Hoberg and Phillips (2010) and calculate sales-based HHI amongst this set of firms. High (low) HHI is the subsample with HHI greater than or equal to (smaller than) the median. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

Panel A: Sort by HHI of rivals in three-digit SIC industry

	High HHI		Low HHI	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.1772***	0.1698***	0.0098	0.0042
	(0.002)	(0.004)	(0.893)	(0.953)
Log(1 + number of own-firm innovation awards)	0.048	0.0737	0.0914	0.0858
	(0.718)	(0.583)	(0.621)	(0.644)
Tobin's Q	0.0293***	0.031***	0.0118	0.0118
	(0.003)	(0.002)	(0.127)	(0.131)
PPE	-0.7248***	-0.7099***	-1.1481***	-1.1478***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash ratio	-0.0913	-0.1481	0.0732	0.0447
	(0.541)	(0.324)	(0.569)	(0.722)
Log(size)	0.2442***	0.2435***	0.2796***	0.2794***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.1119*	-0.1145*	-0.2463***	-0.2367***
	(0.08)	(0.079)	(0.007)	(0.009)
ROA	-0.0096	-0.0267	0.1939	0.1907
	(0.954)	(0.873)	(0.133)	(0.141)
Sales growth	-0.0001	-0.0002	-0.0018	-0.0017
	(0.553)	(0.53)	(0.22)	(0.228)
R&D to assets	-1.1597**	-1.4219***	-0.4898*	-0.5547*
	(0.012)	(0.004)	(0.069)	(0.058)
Log(1 + patent count)	0.0205	0.0118	0.0591***	0.0539***
	(0.345)	(0.597)	(0.003)	(0.007)
Industry M&A indicator		0.3009***		0.1609
		(0.002)		(0.406)
HHI		-0.3894**		0.6605
		(0.019)		(0.108)
Industry sales growth		0.0001		-0.2119*
		(0.997)		(0.093)
Log(1 + industry patent count)		0.0425**		0.0493***
		(0.015)		(0.003)
Intercept	-7.1217***	-7.334***	-7.9297***	-8.2539***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	28,976	28,976	27,768	27,768
-2 Log Likelihood	14,299	14,265	14,644	14,633

Panel B: Sort by HHI of rivals defined using Hoberg and Phillips (2010) data				
	High HHI		Low HHI	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.1318**	0.1286**	0.1071	0.1169
	(0.028)	(0.033)	(0.198)	(0.159)
Log(1 + number of own-firm innovation awards)	-0.1177	-0.0879	0.1028	0.1368
	(0.494)	(0.614)	(0.612)	(0.501)
Tobin's Q	0.0321**	0.0329***	0.0061	0.0068
	(0.01)	(0.01)	(0.697)	(0.667)
PPE	-0.926***	-0.9546***	-0.6395***	-0.5741**
	(0.000)	(0.000)	(0.004)	(0.013)
Cash ratio	0.41***	0.3823**	-0.1993	-0.2721
	(0.008)	(0.013)	(0.246)	(0.115)
Log(size)	0.2375***	0.2368***	0.2798***	0.277***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.2129**	-0.2155**	-0.4418***	-0.4452***
	(0.033)	(0.032)	(0.000)	(0.000)
ROA	0.0325	0.041	0.5934***	0.5883***
	(0.891)	(0.868)	(0.001)	(0.002)
Sales growth	0.0011	0.0011	-0.0018	-0.0027
	(0.473)	(0.486)	(0.316)	(0.361)
R&D to assets	-0.8023**	-0.9014**	-0.0439	-0.1462
	(0.028)	(0.022)	(0.897)	(0.69)
Log(1 + patent count)	0.0908***	0.0885***	0.0318	0.0191
	(0.000)	(0.000)	(0.255)	(0.493)
Industry M&A indicator		0.2967**		0.2666*
		(0.014)		(0.098)
HHI		-0.2948		0.0252
		(0.167)		(0.913)
Industry sales growth		-0.1602		0.0527
		(0.319)		(0.431)
Log(1 + industry patent count)		0.011		0.0807***
		(0.536)		(0.001)
Intercept	-6.9797***	-7.2576***	-8.0824***	-8.1922***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	21,549	21,549	18,813	18,813
-2 Log Likelihood	10,916	10,898	9,129	9,110

Table 8: Logit Regression Analysis of Being an Acquirer - CEO Overconfidence

This table reports coefficient estimates from logit regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is M&A indicator, which is equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise. In Panel A, we sort the sample by whether or not the CEO is overconfident: an overconfident CEO retains exercisable stock options that are more than 67% in the money. In Panel B, we sort the sample by whether or not the CEO is overconfident: an overconfident CEO retains exercisable stock options that are more than 100% in the money. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

Panel A: Define an overconfident CEO if they retain exercisable stock options that are more than 67% in the money

	Overconfident CEOs		Others	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.2646***	0.2598***	0.0449	0.0451
	(0.002)	(0.002)	(0.373)	(0.368)
Log(1 + number of own-firm innovation awards)	0.2171	0.2102	-0.0297	-0.0034
	(0.292)	(0.308)	(0.802)	(0.977)
Tobin's Q	0.0518**	0.0534**	0.0124**	0.0129**
	(0.016)	(0.014)	(0.03)	(0.026)
PPE	-1.2122***	-1.1804***	-0.8671***	-0.8791***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash ratio	-0.2625	-0.281	0.0593	-0.0141
	(0.359)	(0.323)	(0.549)	(0.887)
Log(size)	0.213***	0.2046***	0.2579***	0.2575***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.2404	-0.2407*	-0.2017***	-0.1985***
	(0.101)	(0.098)	(0.001)	(0.001)
ROA	0.1744	0.2574	0.128	0.1168
	(0.589)	(0.436)	(0.157)	(0.189)
Sales growth	0.0011	0.0006	-0.0005	-0.0005
	(0.874)	(0.927)	(0.248)	(0.251)
R&D to assets	-0.5125	-0.6573	-0.5259**	-0.6862***
	(0.511)	(0.415)	(0.021)	(0.008)
Log(1 + patent count)	0.0147	0.0151	0.0653***	0.0518***
	(0.618)	(0.602)	(0.000)	(0.002)
Industry M&A indicator		1.0589***		0.1846**
		(0.000)		(0.026)
HHI		0.1179		-0.1604
		(0.667)		(0.242)
Industry sales growth		0.129		-0.0098
		(0.359)		(0.781)
Log(1 + industry patent count)		0.0183		0.046***
		(0.45)		(0.000)
Intercept	-8.084***	-9.018***	-7.1749***	-7.272***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	8,118	8,118	53,039	53,039
-2 Log Likelihood	5,461	5,422	25,400	25,362

Panel B: Define an overconfident CEO if they retain exercisable stock options that are more than 100% in the money				
	Overconfident CEOs		Others	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.3116***	0.3156***	0.0296	0.0279
	(0.000)	(0.000)	(0.553)	(0.574)
Log(1 + number of own-firm innovation awards)	-0.0069	0.0026	0.0984	0.1284
	(0.971)	(0.989)	(0.418)	(0.292)
Tobin's Q	0.0539**	0.0552**	0.0132**	0.0137**
	(0.026)	(0.022)	(0.026)	(0.021)
PPE	-1.3158***	-1.3307***	-0.8591***	-0.8634***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash ratio	-0.4458	-0.4803	0.0771	0.0111
	(0.171)	(0.138)	(0.416)	(0.908)
Log(size)	0.2225***	0.2117***	0.2573***	0.2566***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.2218	-0.2212	-0.2006***	-0.1957***
	(0.188)	(0.186)	(0.000)	(0.001)
ROA	-0.6052	-0.5688	0.1814*	0.1714*
	(0.101)	(0.131)	(0.063)	(0.077)
Sales growth	0.0559	0.051	-0.0005	-0.0005
	(0.272)	(0.276)	(0.256)	(0.256)
R&D to assets	0.8884	0.7409	-0.6343***	-0.7952***
	(0.213)	(0.33)	(0.004)	(0.001)
Log(1 + patent count)	-0.0126	-0.0066	0.068***	0.0555***
	(0.708)	(0.847)	(0.000)	(0.001)
Industry M&A indicator		0.9607***		0.2325***
		(0.000)		(0.005)
HHI		-0.3156		-0.0616
		(0.275)		(0.635)
Industry sales growth		0.2257		-0.0138
		(0.104)		(0.703)
Log(1 + industry patent count)		0.0085		0.0453***
		(0.739)		(0.000)
Intercept	-7.7864***	-8.5334***	-7.2221***	-7.3741***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	7,136	7,136	54,021	54,021
-2 Log Likelihood	4,867	4,834	25,966	25,930

Table 9: Logit Regression Analysis of Being an Acquirer – Corporate Governance

This table reports coefficient estimates from logit regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is M&A indicator, which is equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise. We sort the sample by Gompers, Ishii, and Metrick's (2003) G-index. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

	High G-index		Low G-index	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.1437***	0.1407**	-0.0652	-0.0696
	(0.009)	(0.011)	(0.456)	(0.425)
Log(1 + number of own-firm innovation awards)	0.011	0.0311	-0.0169	0.0244
	(0.934)	(0.816)	(0.942)	(0.918)
Tobin's Q	0.0188	0.0212	0.0352***	0.0358***
	(0.321)	(0.285)	(0.002)	(0.001)
PPE	-0.7451***	-0.748***	-1.0819***	-1.2024***
	(0.004)	(0.004)	(0.000)	(0.000)
Cash ratio	0.1419	0.0237	0.2614	0.1315
	(0.433)	(0.897)	(0.24)	(0.558)
Log(size)	0.2306***	0.2264***	0.2629***	0.2659***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.3209***	-0.3156***	-0.2047*	-0.2034*
	(0.004)	(0.004)	(0.075)	(0.08)
ROA	-0.3616	-0.3464	0.5053*	0.5017*
	(0.223)	(0.252)	(0.053)	(0.059)
Sales growth	-0.0031	-0.0027	-0.0007	-0.0008
	(0.385)	(0.442)	(0.523)	(0.485)
R&D to assets	-0.3971	-0.5146	-0.4419	-0.6565
	(0.378)	(0.278)	(0.381)	(0.217)
Log(1 + patent count)	-0.0077	-0.0181	0.0727**	0.0655**
	(0.726)	(0.427)	(0.013)	(0.031)
Industry M&A indicator		0.5155***		0.2101
		(0.000)		(0.227)
HHI		0.0574		-0.9504***
		(0.774)		(0.001)
Industry sales growth		-0.1154		0.1223
		(0.459)		(0.561)
Log(1 + industry patent count)		0.0388**		0.0212
		(0.044)		(0.382)
Intercept	-7.3776***	-7.6666***	-18.2384***	-17.7255***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	14,099	14,099	10,397	10,397
-2 Log Likelihood	8,964	8,939	6,652	6,628

Table 10: Logit Regression Analysis of Being an Acquirer – Advertising spending

This table reports coefficient estimates from logit regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is M&A indicator, which is equal to one if a firm announces a successful or unsuccessful M&A deal in year t+1; zero otherwise. We sort the sample by whether or not the rival firms have reported advertising expenditures. Definitions of other variables are contained in the Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

	Rival firms without advertising spending		Rival firms with advertising spending	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	0.1697***	0.1688***	-0.1037	-0.0993
	(0.000)	(0.000)	(0.272)	(0.293)
Log(1 + number of own-firm innovation awards)	-0.1131	-0.1023	0.1757	0.206
	(0.414)	(0.463)	(0.299)	(0.231)
Tobin's Q	0.0185***	0.0188***	-0.0316	-0.0254
	(0.001)	(0.001)	(0.167)	(0.254)
PPE	-0.8426***	-0.8369***	-0.9377***	-1.013***
	(0.000)	(0.000)	(0.002)	(0.001)
Cash ratio	0.0274	-0.0217	0.2333	0.0694
	(0.787)	(0.831)	(0.347)	(0.783)
Log(size)	0.2851***	0.2852***	0.2533***	0.2442***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.1624***	-0.159***	-0.5102***	-0.5139***
	(0.003)	(0.003)	(0.000)	(0.000)
ROA	0.1845*	0.1824*	-0.5165*	-0.5068
	(0.057)	(0.06)	(0.087)	(0.101)
Sales growth	-0.0005	-0.0005	0.0579	0.0542
	(0.216)	(0.214)	(0.298)	(0.324)
R&D to assets	-0.5027**	-0.5902***	-0.0469	-0.5728
	(0.011)	(0.009)	(0.936)	(0.388)
Log(1 + patent count)	0.0392**	0.0299	0.0567**	0.0464*
	(0.045)	(0.123)	(0.017)	(0.06)
Industry M&A indicator		0.1951**		0.6083***
		(0.024)		(0.000)
HHI		0.0211		-0.3127
		(0.874)		(0.195)
Industry sales growth		-0.0059		0.0722
		(0.87)		(0.688)
Log(1 + industry patent count)		0.0358***		0.0531**
		(0.000)		(0.012)
Intercept	-7.4934***	-7.6403***	-7.5944***	-7.939***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	48,057	48,057	13,100	13,100
-2 Log Likelihood	23,041	23,022	7,742	7,700

Table 11: Firm Characteristics of Targets

This table reports mean and median of target firm characteristics and deal characteristics, where the median is reported in italic. The sample contains M&A data between 1997 and 2014. % of cash (% of stock) is the percentage of cash (stock) payment for the M&A deal. Definitions of other variables are contained in the Appendix Table A4.

	Target firm whose acquirer's rivals win innovation award in the prior three years	Target firm whose acquirer's rivals do not win innovation award in the prior three years	P-value of difference
Tobin's Q of targets	1.7220	2.1421	(0.000)
	1.4853	*1.5910*	*(0.389)*
Size of targets	878.8023	833.9622	(0.812)
	259.7323	*179.7264*	*(0.065)*
Leverage of targets	0.2284	0.2418	(0.683)
	0.0883	*0.1435*	*(0.367)*
R&D to assets of targets	0.0947	0.0890	(0.701)
	0.0722	*0.0281*	*(0.006)*
Patent count of targets	0.9888	0.4183	(0.000)
	0.6931	*0.0000*	*(0.000)*
Transaction value to assets	1.7581	2.5031	(0.012)
	1.0960	*1.5110*	*(0.034)*
% of cash	0.4500	0.3837	(0.209)
	0.1157	*0.0000*	*(0.214)*
% of stock	0.2717	0.3417	(0.169)
	0.0000	*0.0000*	*(0.159)*
% of tender offer	0.2133	0.2088	(0.927)
	0.0000	*0.0000*	*(0.927)*

Table 12: Logit Regression Analysis of Target Choice - the Overlap between Targets and Rivals

This table reports coefficient estimates from logit regressions. The sample contains public firms' innovation awards and control variables from 1996 to 2013 and M&A activities from 1997 to 2014. The dependent variable is an indicator, which is equal to one if the acquirer bids for a target that is in the same two-digit SIC industry of one of its rivals that win an innovation award; zero otherwise. Definitions of other variables are contained in Appendix Table A4. Regression models include year fixed effects and two-digit SIC industry fixed effects. Numbers in parentheses are p-values based on standard errors that are clustered by industry-year. ***, **, or * represent 1%, 5%, or 10% significance levels.

	Rivals' innovation awards in past three years		Rivals' innovation awards in past year	
	Model 1	Model 2	Model 3	Model 4
Log(1 + number of rivals' innovation awards)	2.0561***	2.1535***	3.5025***	3.4945***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(1 + number of own-firm innovation awards)	0.6023*	0.6818**	1.2429**	1.1203**
	(0.064)	(0.051)	(0.011)	(0.044)
Tobin's Q	-0.0259	-0.0270	-0.0064	-0.0130
	(0.208)	(0.179)	(0.714)	(0.591)
PPE	1.2834	1.4558*	-1.2333	-1.4727
	(0.119)	(0.100)	(0.261)	(0.226)
Cash ratio	1.2648*	0.9475	-0.3910	-0.8782
	(0.085)	(0.184)	(0.713)	(0.433)
Log(size)	0.0739	0.0626	0.0316	0.0355
	(0.344)	(0.414)	(0.763)	(0.722)
Leverage	-1.4262**	-1.4277**	-2.0421	-2.0401*
	(0.033)	(0.034)	(0.109)	(0.098)
ROA	0.7577	0.7065	3.0130***	2.8775***
	(0.192)	(0.220)	(0.002)	(0.004)
Sales growth	-0.0921	-0.0571	-0.0238	-0.0153
	(0.388)	(0.453)	(0.280)	(0.383)
R&D to assets	1.5214	1.1484	3.7736***	3.1789***
	(0.132)	(0.238)	(0.001)	(0.005)
Log(1 + patent count)	-0.0611	-0.0904	-0.2080*	-0.1896
	(0.441)	(0.262)	(0.060)	(0.103)
Industry M&A indicator		-0.2522		-0.0805
		(0.583)		(0.903)
HHI		-1.7288		-2.3803
		(0.128)		(0.246)
Industry sales growth		0.0124		-0.2892
		(0.253)		(0.786)
Log(1 + industry patent count)		0.1379*		0.0361
		(0.077)		(0.793)
Intercept	-12.4301***	-11.9469***	-12.8722***	-11.9627***
	(0.000)	(0.000)	(0.000)	(0.000)
2-digit SIC industry indicators	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
N	5,547	5,547	5,547	5,547
-2 Log Likelihood	1,493	1,493	785	785