Do PE Buyouts Affect Innovation of the Targets' Industry Rivals?

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December 25, 2017

Abstract

This paper investigates the spillover effects of private equity (PE) buyouts on innovation of the targets' public industry rivals. Using patent-based metrics, I find a robust positive effect of PE buyouts on innovation outcomes of the targets' industry peers and direct competitors. Moreover, I argue that the positive effect is causal by constructing an instrumental variable as a proxy for PE firms' industry experience and focus. Finally, I present evidence that PE buyouts affect industry innovation likely through forcing the targets' rivals to become more focused.

*I thank Professor Michael Gofman, Olga Itenberg, Bill Schwert, and Erin Smith for their helpful comments.

1 Introduction

Many studies have examined extensively how and to what extent PE firms add value to target firms in buyouts (e.g., Kaplan, 1989; Lerner, Sørensen, and Strömberg, 2011; Acharya, etc., 2013; Bernstein and Sheen, 2016). In this paper, instead of focusing on individual buyout target, I broaden the context to examine potential real impacts of PE buyouts on innovation of the targets' rivals. This question is important not only because of the rapid growth of PE industry over the last twenty years and the corresponding concerns about its impact on the economy, but also because of the crucial role of innovation in promoting technological progress and economic growth.

There has been surprisingly little attention paid to the broader impacts of PE firms, especially given frequent negative publicity about them hurting economy through large-scale layoffs and bankruptcies at companies under their control. For instance, during the 2012 U.S. presidential election, there were many discussions about how Bain Capital drove companies bankrupt, rid itself of pension obligations, and paid itself lots of dividends. The most recent example is the bankruptcies of many retail chains, such as Gymboree, Payless, rue21 and True Religion. According to a recent Wall Street Journal article[1], the failures of these retail chains are partly because PE firms acquired them with substantial amount of debt and then, with no intention to invest in the businesses, borrowed even more to pay themselves dividends.

In contrast to the negative publicity and impaired welfare mentioned above, in this study I show positive spillovers from PE buyouts onto the target industries. Specifically, using OLS and Poisson model, I find that there is a robust positive association between PE buyouts and innovation of the targets' rivals, measured by patent-based metrics. As Figure 2 shows, five years after the PE investments, each year the target's industry rivals experience, on average, about 7% increase in quantity of innovation, measured by patent counts, and about 5% increase in quality of innovation, measured by cite-weighted patent counts. In addition, by examining the effects of other non-PE-backed acquisitions on innovation of the targets' peers, I find that this positive externality does not exist in general M&A deals but is unique to PE-backed deals.

[1] "PE Takes Fire as Some Retailers Struggle" by Lillian Rizzo, The Wall Street Journal, July 30, 2017.

However, establishing a causal relationship between PE buyouts and the target peers' innovation can be challenging due to inherent selection issues. If the decision of entering into a industry is correlated with the evolution of the industry's future technological progress, the positive association mentioned above would be unable to tell us whether PE firms actually cause these positive spillover effects or they simply select into industries where they expect changes to occur.

To overcome this endogenous industry selection issue, I extract the exogenous part of decision-making process of industry selection and then use the instrumental variable approach to identify the real impacts of PE buyouts on the target peers' innovation. This exogenous part of decision-making process regarding industry selection is precisely summarized by Gompers, Kaplan, Mukharlyamov (2016). They point out "PE firms often have particular industry experience and focus. A successful track record in a particular industry is likely to lead to greater investment focus on a particular sector."

It is well known that PE firms normally focus their investments on a few industries or sectors. As such, PE firms usually know their customers, suppliers, competitors, products, technology, regulations, and other factors that drive the industries in which they specialize. Moreover, unlike venture capital firms, PE firms' industry expertise allows buyout business to be more scalable within an industry (Metrick and Yasuda, 2010). Hence, for PE firms with focus on a particular industry, they are more likely to succeed in that industry, which, in turn, help them raise more funds from LPs and continue to invest in that industry.

What this means for the identification strategy is that some industry selection decisions are made not because PE firms quickly react to changing economic conditions and select into industries where they expect changes to occur, but because of their industry focus and past successful experience, which is arguably independent of industry's future technological progress and can be used as an exogenous source of variation to draw a causal inference.

The instrumental variable in this study is to capture, for a given industry, how many PE firms actually focus on that industry and have successful past experience in that industry. To construct such an instrumental variable, I aggregate the information of individual PE firms' industry focus based on 2-digit SIC industry. Specifically, for a given 2-digit SIC industry, I count the number of PE firms that specialize and invest in that industry during a five-year window prior to the PE-backed deals in question. I then scale that number by the relative size of each 3-digit SIC industry nested in that 2-digit SIC industry (see formal definition in Section 4.2 or Figure 4).

The intuition behind this instrumental variable is: if there are more PE firms that actively and successfully specialize in a 2-digit SIC industry and more companies operate in a particular 3-digit SIC sector nested in that 2-digit SIC industry, it is more likely that there will be more subsequent PE buyouts in that 3-digit SIC sector. In the 2SLS estimation, the effects of PE buyouts are identified from the differences in the number of active industry-experienced PE firms in each 2-digit SIC industry and the differences in the relative size of each 3-digit SIC industry nested in a 2-digit SIC industry. Consistent with this intuition, I find strong evidence that the instrumental variable can predict future PE buyouts.

For the instrument to be valid, it can affect the target peers' innovation only through affecting the probability of subsequent buyouts completion. One concern is that the initial decision of focusing on a particular industry or developing operating expertise for that industry might be endogenous. If a positive correlation exists between the initial decision of selectively focusing on a particular industry and the evolution of that industry's future innovation progress, then the instrumental variable would be unable to identify the effects of PE buyouts. Another concern is that the instrumental variable may be positively correlated with the number of total PE deals during the same time period over which the instrument is defined. However, these two concerns are unlikely to invalidate the instrumental variable for two reasons.

First, these two concerns imply that the positive spillover effects should not depend on actual entry time of PE firms. However, the evidence obtained from Figure 2 is inconsistent with this predication. Figure 2 presents dynamic effects of PE buyouts on industry innovation and none of lead variables are statistically significant, meaning that the effects manifest only after PE investments.

Second, these two concerns also imply that the instrument should affect the corporate innovation in industries where there are no subsequent PE-backed deals. PE firms' industry focus and expertise are measured based on a broader level (2-digit SIC code) while the innovation spillover effect is investigated within 3-digit SIC industries. This provides me with a nice setting to conduct a Placebo test to examine the effects of the instrument on innovation of companies in 3-digit SIC industries where there are no follow-on PE buyouts. The results of Placebo test support validity of the instrument variable (see Section 4.3.2 for detailed discussions).

The results of 2SLS estimation indicate that the positive association between PE buyouts and the target rivals' innovation is causal. Moreover, 2SLS suggests a much stronger effect of PE buyouts. OLS model shows that three years after the buyout transaction, a PE-backed deal, on average, increases number of new patents of companies in the target industry by about 5% each year for about three to four years, whereas 2SLS suggests an increase by over 90%.

This huge difference in the economic significance is resulted from the fact that PE firms that respond to the instrumental variable are systematically different from those firms that do not respond. And the PE firms that typically respond to the instrumental variable are usually successful firms with a good track record in the industries in which they specialize. Since 2SLS can only identify the effects of PE-backed deals that respond to the instrumental variable, it is not surprising that, compared to other PE firms, firms with strong industry expertise have a much greater impact on the buyout target industry.

What leads to this positive spillover? PE-backed deals may cause more follow-on acquisitions in the target industry (Harford, Stanfield, and Zhang, 2016). When there is a more active acquisition market, small firms may optimally choose to become more innovative to increase the bargaining power, and large firms may decide to let small firms conduct R&D and then subsequently acquire the companies that have successfully innovated (Phillips and Zhdanov, 2013). Taken these two findings together, PE-backed deals may spur corporate innovation by creating a more active acquisition market.

Alternatively, given the fact that PE-backed firms themselves become more focused after the buyout transactions (e.g., Muscarella and Vetsuypens, 1990; Opler and Titman, 1993; Lerner, Sørensen, and Strömberg, 2011), through changing the nature of industry's competitive environment, PE-backed firms force the target rivals to shift focus to the areas in which they are most experienced. Since conglomerates are shown to stifle innovation due to inefficiencies of internal capital market on allocating resources to multiple R&D divisions (Seru, 2014), forcing buyout target's rivals to become more focused is likely to be another channel through which PE buyouts increase the industry innovation.

Testing first hypothesis is relatively straightforward. However, directly testing second one can be quite changeling. Ideally, we want to compare companies becoming more focused following PE investments with companies undergoing no change in internal capital market. However, we cannot observe changes in internal capital market for firms that report only one segment even if some of them have multiple R&D divisions undertaking distinct research projects (e.g., Apple, Cisco, and Amazon). This leads me to conduct two indirect tests. First test is to look at the innovation outcomes of the buyout target's direct competitors, a much smaller set than 3-digit SIC industry rivals. This allows us to see if the direct competitors respond more aggressively than other industry rivals. Second test is based on product market competition, given that high competition is expected to reinforce the positive effects of PE buyouts on corporate focus of the target's rivals. I discuss and test these two hypotheses in Section 5 and find evidence supporting "increased corporate focus" hypothesis rather than "more active acquisition market" hypothesis.

This study contributes to a growing literature that explores the broader impacts of PE firms on industry and economy. Bernstein, Lerner, Sorensen, Strömberg (2017) show cross-country evidence that there are positive spillovers from PE investments onto the industries' total production, employment, and capital formation. In addition, they find that industries where PE funds invest appear less exposed to aggregate shocks. Aldatmaz and Brown (2016) find similar evidence that PE investments promote industries' labor productivity, profitability, and capital expenditures. Since innovation is the main engine of growth, this paper complements these two studies by providing a potential explanation as to why PE investments promote industry productivity and growth.

Harford, Stanfield, and Zhang (2016) find that LBOs change the competitive nature of the target's industry, causing industry peers to change the boundary of the firm through acquisitions or strategic alliances. My findings, on the other hand, suggest that companies also become more focused in response to the competitive pressure from PE-backed firms.

The rest of the paper proceeds as follows. Section 2 describes the data and presents summary statistics and Section 3 presents the suggestive evidence from OLS and Poisson model. Section 4 provides evidence from 2SLS. Section 5 discusses potential channels. Section 6 concludes.

2 Sample Selection and Summary Statistics

I combine innovation data from Kogan, Papanikolaou, Seru, and Stoffman (2017)[2], firms' balance sheet data and segment information from Compustat, PE-backed deals and other acquisitions data from Thomson Reuters SDC database, PE buyout targets' competitors information from CapitalIQ, and institutional ownership data from Thomson Financial 13F institutional holdings database. I restrict the sample to firms with at least one successful patent application (patent-producing firm) over the period of 1990-2009. I also exclude utility firms (SIC code 4900-4999), financial firms (6000-6999), and companies with SIC code between 9000-9999 (international affairs and non-operating establishments). The final sample examined in this paper includes 689 PE-backed deals during the period of 1983-2009 and 42,230 firm-years during the period of 1990-2009.

2.1 PE Buyouts Selection

I identify PE-backed deals completed in US during the period from 1983-2009 using Thomson Reuters SDC database. And a deal is PE-backed if it satisfies: i) the acquirer or the acquirer's parent is a PE firm, ii) the shares owned after the transaction are greater than 50%, iii) the shares held by the acquirer before the transaction are less than 50%, iv) transaction value is greater than or equal to $100 million, and v) acquisitions take the form of merger (SDC deal form M), acquisition of majority interest (SDC deal form AM), or acquisition of assets (SDC deal form AA). For the

[2]Their data are available at https://iu.app.box.com/v/patents

first selection criterion, I rely on the business descriptions of acquirer or acquirer's parent provided by SDC. For the fourth selection criterion, restricting deals to relatively large acquisitions allows me to focus on the cases with a potential industry-wide effect. As a robustness test, deals with transaction value between $50 and $100 million are also considered and the results still hold. In addition, I exclude deals in which targets are utility firms (SIC code 4900-4999) and financial firms (6000-6999). For non-PE-backed deals, selection criteria are exactly same as those of PE-backed deals expect for the first selection criterion.

My final sample consists of 689 successful PE-backed deals with 209 PE firms and 10,382 successful non-PE-backed acquisitions. Panel A of Table 1 presents PE-backed deals by year, which shows tremendous growth of PE industry over the sample period of 1983-2009. Deals completed before 1990 only constitutes about 7% of all sample deals whereas about 70% of all deals took place after 2000. Given all sample deals with transaction value at least $100 million, inflation might contribute to this upward time trend of number of PE-backed deals. However, if this upward trend were simply due to inflation, we should expect to see the number of deals in the last few years of the sample period is twice as many as the number of deals in early years of the sample. However, as Panel A of Table 2 shows, the number of deals in last three years of the sample period is about 15 times the number of deals in the first three years of the sample period.

Panel B of Table 1 presents the distribution of PE-backed deals across the Fama-French 49 industries. The four industries that PE firms invest most frequently are Business Services, Hotel and Restaurants, Communication, and Retail with 67, 41, 41, and 40 deals, respectively. PE firms' least favorite industries are Coal, Non-Metallic and Industrial Metal Mining, and Precious Metals with no investment at all. The distribution of PE-backed deals across industries shows that PE-backed deals tend to cluster in some industries.

Whether this tendency of clustering causes any issue in this study depends on the innovation intensity of the industries in which PE-backed deals concentrate. Figure 1 shows the relation between innovation intensity and PE investment frequency. Innovation intensity is calculated by first computing the industry-year innovation intensity as the average number of patents for all patent-producing firms in each of Fama-French 49 industries in each year and then measure each industry's innovation intensity as its time-series mean during 1990–2009. PE investment frequency is the unique rank, with ties broken arbitrarily, of the frequency of PE firms investing in each of Fama-French 49 industries during 1990–2009, and the unit of calculating the frequency is industry-year.

As we can see in Figure 1, among four PE firms' most favorite industries (Business Services, Hotel and Restaurants, Communication, and Retail), except for Communication industry with innovation intensity above average level, the rest of them are actually least innovative industries. In fact, upper-left corner is much more crowded than upper-right corner in Figure 1, which implies that, compared to highly innovative industries, PE firms pay more attention to industries with low innovation intensity. This, to some extent, mitigates the concerns that positive effects of PE investment on industry innovation are driven by PE-backed deals clustering in highly innovative industries. It is also worth noting that in Figure 1 Aircraft and Computer Hardware industry really stand out with average number of patents much more than other industries. To eliminate the potential outlier effect due to this, I exclude companies from Aircraft and Computer Hardware, and the results still hold.

Table 2 presents summary statistics of PE buyout deals. Average transaction value is about $64 million dollars. About 50% of all PE-backed deals are leverage buyout transactions and 30% of those deals have buyout targets that are public companies. In addition, as indicated by the variable PE, 26% firm-years are in the same 3-digit SIC industry as the targets of successful PE-backed deals when the deals are effective.

2.2 Measuring Innovation

Existing literature uses R&D spending and patent information as two proxies to capture firm's innovation. R&D spending captures innovation input and patent information measures innovation output. Between the two measures, patenting activity is considered a better proxy, because it reflects productivity of R&D and the quality of innovation. Therefore, following previous studies (e.g., Hall, Jaffe, and Trajtenberg, 2001; 2005) I use patent information to measure innovation.

The innovation variables are constructed based on Papanikolaou, Seru, and Stoffman (2017), in which they provide a patent database that covers all utility patents issued by the USPTO between 1926 and 2010. This patent database contains patent's information regarding filling date, grant date, technology class, and number of citations. Since the application year is closer to the time of the actual innovation, I then construct patent-based variables based on filling date rather than grant date. In addition, all patents filed in 2010 do not have technology class information. Therefore, the final sample contains patents filed between 1990 and 2009.

The first measure of innovation output is the number of granted patents filed by a firm in a given year. However, a simple count of number of patents is subject to truncation problem, because the patents appear in the database only after they are granted and the lag between filing date and grant date is substantial, which is about 2 years on average (Hall, Jaffe, and Trajtenberg, 2001). And this truncation problem becomes more severe as we approach to the last few years of sample period. What we see in the data is that there are a much smaller number of patents after 2004.

And this significant decline in number of patent after 2004 is largely due to the reason that many patent applications are still under review and have not yet been granted by 2010. To correct for the truncation bias, following Hall, Jaffe, and Trajtenberg (2001), I first estimate a empirical distribution of lag time for the patents that are filed between 1999 and 2004. I then, for patents filed between 2005 and 2009, compute adjusted patent counts filed in year t, P_t', as

$$P_t' = \frac{P_t}{\sum_{s=0}^{2009-t} W_s}, \quad t = 2005, ..., 2009 \tag{1}$$

,where W_s is the percentage of patents granted in s years, which is estimated based on patents filed between 1999 and 2004 and P_t is the number of patents that we can observe or have been granted. Adjusted patent counts, P_t', is winsorized at the 99th percentiles to prevent any influence of extreme outliers.

A problem associated with patent counts as a measure of innovation is that number of patent simply reflects the quantity of innovation output but fails to capture the quality of innovation. Trajtenberg (1990) points out that a simple count of patents is unable to distinguish breakthrough innovations from incremental technological discoveries. Thus, by using citation information, I construct cite-weighted patent counts as my second measure to capture technological and economic significance of patent innovations.

Different technologies and time periods can have substantial differences in citation rates. Therefore, a simple comparison of raw citations ignores lots of useful information and can be misleading in many cases. Cite-weighted patent counts are not simply scaled by future citations that each patent receives but scaled by scaled citations. To take this potential heterogeneity in citation rates into consideration, following Hall, Jaffe, and Trajtenberg (2001), I compute scaled citations by dividing citation counts of each patent by the average number of citations received by all patents that are granted in the same year and technology class.

Table 2 presents the firm-year summary statistics of the innovation variables. Patent counts and cite-weighted patent counts are both very skewed: the mean values of patent counts and cite-weighted patents are 15.17 and 14.29, respectively, but the median value for both of these two measures is 0. Since the distributions of patent counts and cite-weighted patent counts are highly right skewed, I use $ln(Patent)$ and $ln(Cite)$ as main innovation measures in my analysis, where ln(Patent) = ln(1+Patent counts) and ln(Cite) = ln(1+Cite-weighted patent counts).

2.3 Firm Characteristics and Measures of Corporate Focus

To control for firm and industry characteristics that may affect a firm's innovation, following the innovation literature, I include a series of control variables. These control variables are size (measured by the natural logarithm of total assets), return on assets (ROA) (measured by operating income before depreciation and amortization divided by total assets), R&D expenditures (measured by natural logarithm of R&D expenditures divided by total assets plus one), book leverage, Lerner index, a proxy for product market competition, (measured by operating income before depreciation and amortization divided by total sales), market to book ratio, and institutional 14 ownership.

Since some companies do not report R&D expenditures every year, I set missing values of those companies' R&D expenditures to zero. All control variables are winsorized at the 1st and 99th percentiles to prevent any influence of extreme outliers. Panel B of Table 2 reports the descriptive statistics of these control variables.

I extract firms' segment accounting and financial information from Compustat segment files. The simplest measure of corporate focus is the number of segments for a firm in a given year. Panel B of Table 2 shows that 65 % of patent-producing companies are single-segment companies. And on average, each firms has 1.89 segments.

Following Comment and Jarell (1995), I construct another two measures of corporate focus based on Herfinahl index. Before I compute these two measures, following Berger and Ofek (1995), I drop firm-years if the sum of the segment sales is not within 1% of the total sales, which yields 19,603 patent-producing firm-years during the period of 1990-2009. First measure is a revenue-based Herfindahl index, which is calculated as

$$Foc\_R_{it} = \sum_{j=1}^{N_{it}} \left(X_{ijt} / \sum_{j=1}^{N_{it}} X_{ijt} \right)^2 \tag{2}$$

,where X_{ijt} is the revenue in segment j of company i in year t and N_{it} is the number of segments of company i in year t.

Second measure, Foc_A_{it}, is a asset-based Herfindahl index and can also be calculated by equation (2) with X_{ijt} being replaced by the book value of identifiable assets in segment j of company i in year t. Using Herfindahl index allows us to see how concentrated revenues or assets are in just a few of a company's business segments. Thus, for all three measures of corporate focus, a higher value implies more focus a company is. Panel B of Table 2 presents summary statistics of three corporate focus measures.

3 Suggestive Evidence

3.1 Dynamic Effects of PE Buyouts on Industry Innovation

This section investigates how PE buyouts around a certain year affect corporate innovation in that year. Studying the dynamic effects of PE buyouts is informative for three reasons. First, the real consequences of PE buyouts on industry innovation caused by the actual entry of PE firms could manifest over several years after PE investments. Second, it allows us to know how long it takes for the effects to take place. Since innovation itself is a time-consuming process and it might also take time for the target peers to respond and make some necessary changes to accommodate innovation activities, it is unlikely that we see the effects take place immediately after the PE firms enter into some industry. Third and more importantly, investigating the dynamic effects of PE buyouts helps us detect if there is any reverse causality problem.

In Figure 1, I present how the PE buyouts at different points in time affect patent counts and cite-weighted patent counts in year t. The graphs represent coefficients plots (and their associated 95% confidence intervals as represented by the vertical bars) from the following specification:

$$ln(Patent_{ijt}) = \alpha_0 + \sum_{n=-2}^{n=8} \gamma_n PE_{j,t-n} + \beta' X_{ijt} + \tau_{i(j)} + \mu_t + \varepsilon_{ijt} \quad (3)$$

,where $ln(Patent_{ijt})$ is natural logarithm of either patent counts or cite-weighted patent counts plus one for firm i in industry j in year t, in which a patent application was submitted. $PE_{j,t-n}$ is a dummy variable indicating if there are PE-backed deals completed in 3-digit SIC industry j in year $t-n$. X_{ijt} is a vector of control variables. The specification is estimated using OLS and includes either firm fixed effects (τ_i) or 3-digit SIC industry fixed effects (τ_j), and year fixed effects (μ_t).

Regardless of model specifications (firm fixed effects vs. industry fixed effects), the dynamic effects of the PE buyouts on both patent counts and cite-weighted patent counts in year t show very similar pattern. First, the coefficients on lead variables (PE buyouts completed after year t) are all statistically insignificant. If PE buyouts lead to a change in innovation but not vice versa, then the

PE-backed deals should not have any effect on corporate patenting activities before the deals even exist. This is indeed what we observe in both graphs in Figure 1, suggesting that reverse causality is not very plausible in this study.

Second, under both model specifications, we do not see the effects manifest immediately after the PE investments. Instead, it takes at least five years for the coefficients to become significant at 5% level. This is consistent with our intuition that first, innovation process is time-consuming and second, it might take time for the buyout target's peers to respond and make some necessary changes to accommodate innovation activities.

3.2 Evidence from OLS and Poisson Model

This section presents suggestive evidence from OLS and Poisson model. The baseline specification of OLS is

$$ln(Patent_{ij,t+k}) = \alpha_0 + \gamma PE_{j,[t-2,t]} + \beta' X_{ijt-2} + \tau_i + \mu_t + \varepsilon_{ijt},\ k = 3,4,5 \tag{4}$$

,where $ln(Patent_{ij,t+k})$ is natural logarithm of either patent counts or cite-weighted patent counts plus one for firm i in industry j in year $t+3$, $t+4$, or $t+5$, $PE_{j,[t,t-2]}$ is a dummy variable indicating if there are PE-backed deals completed in 3-digit SIC industry j between year t and $t-2$ (a three-year window), X_{ijt-2} is a vector of control variables in year $t-2$ defined in Table 2. The specification is estimated using OLS and includes firm fixed effects (τ_i) and year fixed effects (μ_t). All control variables are lagged by two years to reduce simultaneity concerns, and all time-invariant firm and industry characteristics that may influence corporate innovation activities are controlled for with firm fixed effects.

To explore the potential effects of other acquisitions on target peers' innovation, I also use the baseline specification with $PE_{j,[t,t-2]}$ being replaced by *non-*$PE_{j,[t,t-2]}$, which is a dummy variable indicating if there are other acquisitions completed in 3-digit SIC industry j between year t and $t-2$. This comparison between PE-backed deals and other M&A deals allow us to see if the effect results from all types of M&A deal or is unique to PE-backed deals.

In addition to OLS, I also employ a quasi-maximum likelihood (QML) Poisson model to explore the effects of PE buyouts, which assumes that the expected number of patents or citation counts is an exponential function of the PE buyouts and other explanatory variables. More specifically,

$$E[Patent_{ij,t+k}|PE_{j,[t-2,t]},X_{ijt-2}] = exp\{\alpha_0 + \gamma PE_{j,[t,t-2]} + \beta' X_{ijt-2} + \tau_i + \mu_t + \varepsilon_{ijt}\},\ k = 3,4,5 \quad (5)$$

,where $Patent_{ij,t+k}$ is either patent counts or cite-weighted patent counts for firm i in industry j in year $t+3$, $t+4$, or $t+5$ and all other variables are defined same as those in OLS.

Table 3 presents the estimation results from both OLS and Poisson model.[3] Panel A of Table 3 shows the effects on quantity of innovation output with patent counts as dependent variable. The coefficient estimates on $PE_{[t-2,t]}$ in column (1), (3), and (5) are positive and significant at either the 1% or 5% level, suggesting a positive association between PE buyouts and the target peers' innovation output. In terms of economic significance, PE-backed deals completed between year $t-2$ and year t, on average, increase a target peer's annual number of patent by about 5.2% $(= \frac{4.4\%+5.9\%+5.2\%}{3})$ during the period between year $t+3$ and $t+5$. On the other hand, the coefficient estimates on *non-*$PE_{[t-2,t]}$ in column (2), (4), and (6) are statistically insignificant, suggesting that this positive association is not resulted from general M&A deals but unique to PE-backed deals. To check the robustness of OLS regression results, column (7) through column (9) are the estimation results from Poisson regressions. The coefficient estimates on $PE_{[t-2,t]}$ are all statistically significant at 1% level. Moreover, compared to OLS regressions, they are qualitatively similar but quantitatively much larger, which is mainly because the distribution of patent counts is highly right-skewed.

Panel B of Table 3 shows the impacts on quality of innovation output with cite-weighted patent

[3]In an untabulated analysis, I repeat OLS analysis with dependent variables: $ln(Patent_{t+6})$, $ln(Patent_{t+7})$, $ln(Cite_{t+6})$, and $ln(Cite_{t+7})$. The coefficient estimate on $PE_{[t-2,t]}$ for $ln(Patent_{t+6})$ is statistically significant at 5% level. And it is quantitatively and qualitatively similar to the estimates in column (1), (3), and (5) in Panel A. The coefficient estimates on $PE_{[t-2,t]}$ for $ln(Patent_{t+7})$, $ln(Cite_{t+6})$, and $ln(Cite_{t+7})$ are statistically insignificant.

counts as dependent variable. The coefficient estimates on $PE_{[t-2,t]}$ in column (1) and (3) are positive and significant at either the 1% or 5% level. Although the coefficient estimate in column (5) is not significant, this does not keep us from interpreting the results from column (1) and (3) as a positive association between PE buyouts and quality of the target peers' innovation output. However, the coefficient estimates on *non-*$PE_{[t-2,t]}$ in column (2), (4), and (6) are statistically insignificant, suggesting that this positive association is, again, unique to PE-backed deals. Similar to the pattern in Panel A, compared to OLS specification, the coefficient estimates on $PE_{[t-2,t]}$ from Poisson regressions (column 7-9) in Panel B are qualitatively similar but quantitatively much larger.

3.3 Robustness Checks

Table 11 conducts various robustness tests. Harford, Stanfield, and Zhang (2016) suggest that following LBOs, the targets' peers may acquire other firms to change their firm boundaries in response to the competitive pressure from firms that undertake LBO. If this is also the case in my study, then the innovation output of targets' peers may increase mechanically. To address this concern, I exclude firms that become acquirers following PE investments. Column (1) and (2) show that the results sill hold without companies subsequently becoming acquirers.

In column (3) and (4), I exclude Computer Hardware and Aircraft industry (based on FF-49 classification) to eliminate concern that the results may be driven by these two most innovative industries. In column (5) and (6), I show the effect of PE buyouts whose targets are private companies. Conducting this robustness check is because I study the effects of PE buyouts on the targets' public peers and the results may be driven by public-to-private transactions. As shown in column (5) and (6), the results still hold with private buyout targets. The last robustness check is to see if different definition of buyout targets' peers affects the results. In column (7) and (8) the target's peers are defined based on 4-digit SIC industry and the results still hold.

4 Evidence from 2SLS

4.1 Identification

So far I have shown a robust positive association between PE buyouts and subsequent innovation outcomes of the target's peers. Identifying the effects of PE buyouts on the target peers' innovation, however, can be challenging due to inherent selection issues that arise from the decision made by PE firms regarding which industry to invest in. It is possible that the PE firms quickly respond to changing economic conditions and select into industries where they expect changes to occur. If this is the case, then the decision of investing in a particular industry might be correlated with future innovation activities in that industry. Therefore this potential endogenous decision-making process regarding industry selection prevents us from drawing causal conclusions from either OLS or Poisson model.

In spite of the endogenous part of decision-making process, there is an exogenous reason as to why PE firms decide to enter into a industry, and this exogenous reason is precisely summarized by Gompers, Kaplan, Mukharlyamov (2016). They point out "PE firms often have particular industry experience and focus. A successful track record in a particular industry is likely to lead to greater investment focus on a particular sector." To elaborate on their point, I first discuss how PE firms add value to buyout targets, which is extensively studied in the finance literature.

Buyout transactions from the 1980s create value mainly through stronger managerial incentives, pressure on managers from high leverage, and active oversight by smaller boards compared to public company boards (e.g., Lichtenberg and Siegel, 1990; Smith, 1990; Kaplan, 1989). In addition to financial and governance engineering, Kaplan and Stromberg (2009) claim that PE firms also employ operational engineering to create value.

Through the operational engineering, PE firms differentiate themselves by developing industry and operating expertise to improve target's corporate strategies and operating efficiency. Acharya, etc. (2013) show that deals with partners who have a strong operational background (e.g., ex-industry managers or ex-consultants) generate significantly higher outperformance. Bernstein and

Sheen (2016) also present similar evidence. Their study documents that by bringing industry expertise, PE firms significantly improve store-level operations in the restaurant industry.

Therefore, PE firms normally focus their investments on a few industries or sectors. As such, a PE firm knows the customers, suppliers, competitors, products, technology, regulations, and other factors that drive the industries in which the firm specializes.

In addition to operational engineering, Metrick and Yasuda (2010) present theoretical argument and empirical evidence that the extensive industry expertise of PE firms makes the buyout business more scalable within an industry. What this means is that for PE firms with strong industry focus and expertise, they are more likely to succeed, which, in turn, help them raise more funds from LPs and continue to invest in the industries in which they specialize. Thus, industry focus and experience of PE firms are employed as an exogenous source of variation to identify the effects of PE buyouts on industry innovation.

In Figure 3, I present the relation between fraction of experienced deals and PE firms' total deals during the period of 1983 - 2009. 209 PE firms are divided into five groups according to their total deals. Experienced deals are defined based on the number of deals invested by same PE firm in the same industry.

Green, red, and blue bars represent deals that are invested by same PE firms in same 2-digit SIC industry for more than twice, three times, and four times, respectively. Figure 3 shows that for PE firms with 11 deals or more, even under the most stringent definition of experienced deals, fraction of experienced deals is over 50%. If we only consider the loosest definition of experienced deal, except for young and unsuccessful PE firms (with 5 deals or fewer), experienced deals constitute over 90% of total deals in all groups of PE firms. Thus, Figure 3 provides clear evidence that individual PE firms are inclined to concentrate in just a few industries.

Another feature of Figure 3 is that, under all three definitions of experienced deals, we can observe a strong positive correlation between the fraction of experienced deals and total deals. This positive correlation implies that as PE firms grow, more of their deals are experienced deals, suggesting that past successful deals indeed lead to more deals in the same industry.

4.2 Constructing the Instrumental Variable and Empirical Design

The general idea for the instrumental variable in this study is to capture, for a given industry, how many PE firms actually focus on that industry and have successful past experience in that industry. As more of such PE firms exist for a given industry, we would expect to see more subsequent buyout deals in that industry.

Before I present the instrumental variable, it is useful to introduce some preliminary variables upon which the instrumental variable is built. A PE firm is considered a industry-experienced or industry-focused in a 2-digit SIC industry k at time t if it has completed at least two deals in industry k by time t. Using 2-digit SIC industry instead of 3-digit is because the expertise or skills required for a particular industry is better represented by a 2-digit SIC code. Using 3-digit SIC code to reflect industry focus would unnecessarily induce a very noisy measure.

$Num\_Experienced_{kt}$ is defined as the number of industry-experienced PE firms that invested in a 2-digit SIC industry k in year t. W_{jt} is the ratio of the number of firms in a 3-digit SIC industry j to total firms of its corresponding 2-digit SIC industry in year t. It is intended to capture the relative size of each 3-digit SIC industry nested in a 2-digit SIC industry. With W_{jkt} and $Num\_Experienced_{kt}$, I then construct the instrumental variable, Exp_{jt}, for each 3-digit SIC industry j in each year t as[4]:

$$Exp_{jt} = \sum_{t-7 \leqslant \tau \leqslant t-3} Num\_Experienced_{k\tau} * W_{jt-3} \tag{6}$$

Given PE firms' relative long investment horizon, I use a five-year window $[t-7, t-3]$ to capture how many PE firms that currently focus on a particular industry. In addition, the reason that the time interval ends in year $t-3$ is intended to avoid overlapping main variable $PE_{[t-2,t]}$.

And the intuition behind this instrumental variable is: if there are more PE firms focusing on a particular industry (2-digit SIC) and having successful track records in that industry, and more

[4]In an untabulated analysis, I define the instrumental variable without scaling it by the relative size of each 3-digit SIC industry, that is, $Exp_{jt} = \sum_{t-7 \leqslant \tau \leqslant t-3} Num\_Experienced_{k\tau}$. The results of 2SLS are quantitatively and qualitatively similar.

companies operate in a particular sector (3-digit SIC) within that industry, it is more likely that there will be subsequent buyout deals in that sector (3-digit SIC). Figure 4 provides a timeline to illustrate how the instrumental variable is constructed.

To implement the instrumental variables approach, I estimate the following first-stage regression:

$$PE_{j,[t-2,t]} = \alpha_0 + \gamma Exp_{jt} + \beta' X_{ijt-2} + \tau_i + \mu_t + \varepsilon_{ijt}, \tag{7}$$

and the second-stage estimates the impact of PE buyouts on industry innovation:

$$ln(Patent_{ij,t+k}) = \alpha_0 + \gamma \widehat{PE_{j,[t-2,t]}} + \beta' X_{ijt-2} + \tau_i + \mu_t + \varepsilon_{ijt},\ k = 3,4,5 \tag{8}$$

,where $\widehat{PE_{j,[t-2,t]}}$ is the predicated value from (7). γ captures the causal effect of PE buyouts on industry innovation outcomes. I implement the instrumental variable estimator using two-stage least squares (2SLS).

4.3 Validity of the Instrumental Variable

4.3.1 Industry Focus and Subsequent PE Buyouts

For an instrumental variable to be valid, it must satisfy relevance and exclusion condition. Table 4 examines the relevance condition and presents the first stage results of 2SLS. The analysis unit in Column (1) through (3) is industry-years. Since both main variable $PE_{[t-2,t]}$ and instrumental variable Exp_t are defined on industry level, industry-level analysis is most straightforward way to investigate the relation between the two variables. In column (1), the coefficient on Exp_t is positive and significant at 1% level. Consistent with our intuition, for a given industry, the probability of a successful PE buyout during a three-year window ($PE_{[t-2,t]}$) increases when there are more industry-experienced PE firms focusing on that industry. As for the economic significance, Figure 4 shows the predictive margins based on estimates from column (1). The sample mean and median of instrumental variable is 1.35 and 0.19. According to Figure 4, they predict $Pr(PE_{[t-2,t]} = 1) \approx$

0.46 and $Pr(PE_{[t-2,t]} = 1) \approx 0.15$, respectively.

Column (2) adds two industry-level control variables, Lerner Index and Shock, to Logit model, which may have potential impacts on probability of subsequent PE buyout deals. Following Harford (2005), I also construct this variable by measuring shocks to each industry's operating environment using the following firm-level indicators: net income to sales, sales to assets, R&D to assets, capital expenditures to assets, return on assets and sales growth. For each of 3-digit SIC industry and each year, I take the industry median of the absolute (annual) change in each of the above variables. I then construct Shock variable by extracting the first principal component from these six variables, separately, for each industry. With these two control variables, the results still hold.

Column (3), on the top of column (2), include 2-digit industry fixed effects, which inevitably drops industry-years whose industries have no PE-backed deal during the sample period. The coefficient on Exp_t remains significant at 1% level and is quantitatively similar to results in first two specifications. The unit of analysis in column (4) is firm-years. The coefficient on Exp_t is still significant at 1% level but is about half of those obtained in industry-level analyses.

Column (5) presents the first stage of 2SLS. The coefficient on Exp_t is 0.041 and significant at 1% level. Moreover, the corresponding $F\text{-}statistic$ equals 173. Therefore, given the large $F\text{-}statistic$ relative to the threshold of $F\text{-}statistic = 10$, it is unlikely that the 2SLS estimator is biased due to weak instrument problem (Bound, Jaeger, and Baker (1995) and Staiger and Stock (1997)).

4.3.2 Exclusion Restriction and Placebo Test

For the exclusion condition to be satisfied, the instrumental variable can affect industry innovation only through affecting the probability of subsequent successful PE buyouts completion. One concern is that when PE firms first decide to obtain or develop operating expertise for a particular industry or start to shift focus to a particular industry, the evolution of that industry's future technological progress might be one of factors for them to consider. If PE firms indeed take future industry innovation productivity into consideration when making decisions regarding which industries to focus on, then the exclusion condition would be violated. Another concern is that the instrumental variable may be positively correlated with the number of total PE buyouts during the same time period over which the instrumental is defined.

However, these concerns are unlikely to invalidate the instrumental variable. First, evidence obtained from Figure 2 suggests that the effect of PE buyouts on patenting activities depend on the actual PE entry time. If the PE firms' initial decision of selectively focusing on a particular industry is indeed correlated with that industry's future innovation activities, then the effects on industry innovation should not depend on actual entry time of PE firms. Therefore, in such a case, we should expect to see that at least some of the coefficients on lag variables close to entry time (e.g., PE_t, PE_{t-1}, and PE_{t-2}) and lead variables (PE_{t+1} and PE_{t+2}) are statistically significant. But what we observe in the Figure 2 is that the coefficients on PE_{t-2} through PE_{t+2} under all specifications for both measures of innovation output are all statistically insignificant, which suggests that the effects of PE buyouts depend on the actual entry time of PE firms and take time to manifest.

Second, above two concerns also imply that the instrument would affect corporate innovation in industries where there are no subsequent PE buyout deals. Moreover, the PE firms' industry focus and expertise are measured based on a broader level (2-digit SIC code) while the innovation spillover effect is investigated within 3-digit SIC industries. This provides us with a nice setting to conduct a Placebo test. Therefore, to further alleviate the concern of potential violation of exclusion condition, I examine the effects of the instrument variable on corporate innovation outcomes in 3-digit industries where there are no follow-on PE buyout deals during a five-year window, $[t-2, t+2]$, given that the instrument is define over the period $[t-7, t-3]$.

Table 5 presents the results of Placebo test. Panel A shows the effects of instrumental variable on patent counts. Column (1), (3), and (5) are based on full sample, and column (2), (4), and (6) are estimated based on subsample that only contain companies in 3-digit industries where there are no subsequent PE buyouts. The coefficients on instrument, Exp_t, in column (1), (3), and (5) are all significant at 1% level. Given the strong results in the first stage of 2SLS, this is what we expect.

However, the coefficients on instrument, Exp_t, in column (2) and (6) are insignificant and the corresponding coefficient in column (4) is only marginally significant at 10% level with $t = 1.7$. Panel B shows the effects of instrument on cite-weighted patent counts. Consistent with results obtained in Panel A, the coefficients on the instrument estimated based on the subsample that contains no subsequent PE buyouts are all insignificant. Taken the results obtained from Panel A together, these results suggest that the instrumental variable is unlikely to affect industry's future innovation output through other channels other than affecting the probability of subsequent PE buyouts completion.

4.4 Results of 2SLS

Table 6 presents the results from 2SLS estimation. For patent counts as dependent variable, the coefficients on $PE_{[t-2,t]}$ under all three specifications are positive and statistically significant at 1% significance level, as shown in column (1) through (3). For cite-weighted patent counts, the coefficients on $PE_{[t-2,t]}$ in column (4) and (5) are statistically significant at 1% significance level. And the corresponding coefficient in column (6) is only marginally significant. All of these results suggest that the positive association between PE buyouts and industry innovation outcomes is causal. In addition, these results are largely consistent with results from baseline specification, suggesting that the endogeneity issue in this study does not have a dominant impact.

It is also worth noting that the magnitude of the coefficients on main variable $PE_{[t-2,t]}$ from 2SLS is much larger than that from either OLS or Poisson model. For example, the coefficient on $PE_{[t-2,t]}$ from 2SLS with $ln(Patent_{t+3})$ as dependent variable is 0.97 while the corresponding coefficient from OLS is only 0.04. For other specifications, the coefficients from 2SLS is ranging from about 6 to 20 times larger than those from OLS or Poisson model in Table 3. This huge difference in magnitude is mainly resulted from the local average treatment effect, which says that the estimates from 2SLS come only from the subpopulations that respond to the instrumental variable. In this study, the PE firms that respond to the instrumental variable are usually large and successful firms having relatively strong industry expertise. As a result, it is expected that these firms should have a greater impact on the target peers' innovation outcomes.

5 Potential Channels

The empirical findings thus far have established a causal relationship that PE buyouts not only increase the quantity of the target peers' innovation output but also the quality of it. In this section, I explore potential channels for the empirical findings.

5.1 More Follow-on Acquisitions

Harford, Stanfield, and Zhang (2016) find that a LBO deal is associated with more follow-on acquisitions in the target industry either because a LBO changes the competitive nature of the target's industry or because it signals private industry-specific information.

In addition, Phillips and Zhdanov (2013) document that small firms may optimally choose to innovate more to increase the bargaining power when there is a higher chance of being sold out to larger firms. These two findings together indicate that more follow-on acquisitions within the target industry caused by PE buyouts may be a reason that the target peers, especially small firms, become more innovative afterwards. I discuss and test these two hypotheses in Section 5.3 and find evidence inconsistent with this hypothesis.

5.2 Competitive Pressure and Increased Corporate Focus

The standard practice of PE firms is to buy businesses and then, after a substantial improvement in operations, sell them. This buy-to-sell business strategy also means that PE-backed firms rarely operate in multiple loosely related segments. The evidence from 1990s shows that LBO are frequently followed by divestiture of some of the firm's plants or lines of business (e.g., Muscarella and Vetsuypens 1990; Liebeskind and Opler 1992; Liebeskind, Wiersema, and Hansen 1992). Moreover, Opler and Titman (1993) present evidence that LBO firms also tend to be more diversified than firms that do not undertake LBOs. And the most recent evidence from Lerner, Sørensen, and Strömberg (2011) shows that after the buyout transactions, PE-backed firms start to refocus on areas on which the firms have historically been focused, measured by patent portfolios.

Taken all these findings together, for PE-backed firms, we see this transition from relative diversified companies to more focused firms. And this transition may alter the nature of competitive environment and put pressure on the target's peers to become more focused as well. The implication of this on the innovation of buyout target's rivals is documented by Seru (2014) who presents the causal evidence that organizations with a centralized resource allocation process are shown to foster mediocrity in their divisional R&D activities due to inefficiencies of internal capital market. Therefore, an alternative hypothesis is that through forcing the target's rivals to become more focused, PE buyouts increase the industry innovation productivity.

To test this hypothesis, ideally, we want to compare companies becoming more focused following PE investments with companies undergoing no change in internal capital market. However, we cannot observe changes in internal capital market for firms that report only one segment even if some of them have multiple R&D divisions undertaking distinct research projects (e.g., Apple, Cisco, and Amazon). In addition, for some companies that report two segments and one of them is financial services (e.g., Ford), the measures of corporate focus in this paper are unable to capture the dynamic of their internal capital markets.

As a result, I conduct two indirect tests. First test is to look at the innovation outcomes of the buyout target's direct competitors, a much smaller set than 3-digit SIC industry. If more focused buyout targets are able to alter the nature of competitive environment, we should expect the different impacts on closet competitors than on loosely related industry rivals. With the competitors data hand-collected from CapitalIQ, I examine the impact of PE buyouts on the targets' direct competitors.

Second test is based on product market competition. Since high competition is expected to reinforce the positive effects of PE buyouts on corporate focus of the target's rivals, I examine if positive spillover effects of PE buyouts on industry innovation are also more pronounced in more competitive markets. If more focused industry rivals is indeed a channel through which PE buyouts affect innovation of the targets' rivals, we should also expect a stronger effect of PE buyouts on targets' innovation in more competitive markets.

5.3 Empirical Tests

5.3.1 More Follow-on Acquisitions

To test if more subsequent M&A deals is an explanation for the empirical findings in this paper, the most straightforward way is to check if other non-PE-backed deals are also associated with more following acquisitions in the targets industry. The results in Table 3 suggest that non-PE-backed acquisitions have no impacts on the target peers' patenting activities. Therefore, if PE-backed and non-PE-backed deals both lead to a more active M&A market in the target industry, it would be not reasonable to attribute the empirical findings to this reason.

Table 8 presents the effects of both of PE-backed and non-PE-backed deals on the probability of following acquisitions in the target industry in one year, two years, and three years, respectively. Estimated by Logit model, the coefficients on both $PE_{[t-2,t]}$ and $non\text{-}PE_{[t-2,t]}$ under all specifications are positive and significant at 1% level, suggesting that PE-backed and non-PE-backed can both lead to more acquisitions in the target industry during the following three years. Moreover, when comparing the coefficient on $non\text{-}PE_{[t-2,t]}$ with that on $PE_{[t-2,t]}$ for same dependent variable, $non\text{-}PE_{[t-2,t]}$ always has a larger predictive power. Taken together, these results are largely inconsistent with the hypothesis that more subsequent acquisitions caused by PE-backed deals is the underlying channel through which PE buyouts affect the target industry innovation.

5.3.2 Competitive Pressure

To test the impact of PE buyouts on the targets' direct competitors, I collect targets' competitors information from CapitalIQ. Many of PE buyout targets are private companies and some deals took place long time ago. In addition, some buyout targets do not have public competitors reported in CapitalIQ. As a result, I was only able to identify competitors for 273 out of 689 targets. For all the public competitors provided by CapitalIQ for a given buyout target, I manually check them on Google to select those that exist at the time when the deal took place.

Table 8 presents the test results through OLS. Compared to the baseline results in Table 3, the magnitude on average is about four times larger. The more pronounced impact on direct competitors than on other loosely related industry rivals is consistent with the hypothesis that more focused buyout targets put competitive pressure on their rivals. This also provides additional evidence that the observed better innovation outcomes are not because of industry selection but the actual impacts from PE investments. Otherwise we should not expect there is any difference in the magnitude between direct competitors and loosely related industry rivals. In the next section, I present direct evidence that this competitive pressure also forces the targets' rivals to become more focused.

5.3.3 Increased Corporate Focus and Product Market Competition

To test if increased corporate focus of the target peers explain the empirical findings, I first examine if both PE-backed and non-PE-backed deals are associated with the target peers becoming more focused subsequently. Table 8 presents the test results from OLS. The three measures of corporate focus are number of segment (Num_seg), a revenue-based Herfindahl index (Foc_R), and a asset-based Herfindahl index(Foc_A). Since 65% of companies in the sample only have one business segment, the distributions of all three measures of corporate focus are highly skewed. As a result, I take natural logarithm of all three measures. Under all three measures, the coefficients on $PE_{[t-2,t]}$ are positive and significant at either 1% or 5% level, implying a positive effect of PE buyouts on corporate focus of the target's rivals.

More importantly, the coefficients on $non\text{-}PE_{[t-2,t]}$ are all insignificant, which is consistent with the findings that other types of acquisitions have no impacts on the target ravels' innovation outcomes. In terms of the magnitude of the coefficients, PE buyouts on average increase the corporate focus by about 10% of standard deviation each year for three years starting from year $t+3$.

To test the effects of interaction between product market competition and PE buyouts, I interact $PE_{[t-2,t]}$ with High, Med, and Low. High, Med, and Low indicate the level of product market competition for each 3-digit SIC industry. Since the lower value of the Lerner index implies more intense product market competition, High, Med, and Low equals one if the Lerner Index lies in the bottom, medium, and top tercile, respectively, of its empirical distribution. I drop $PE_{[t-2,t]}$ dummy variable to avoid perfect multicollinearity. In addition, since High, Med, and Low are time-invariant, they would be absorbed by firm fixed effects if added to regression. Thus I drop them as well.

Table 9 presents results of the effects of PE buyouts on corporate focus when interacted with product market competition. Under all specifications, the coefficients on either $PE_{[t-2,t]} \times High$ or $PE_{[t-2,t]} \times Med$ are significant at either 5% or 1% level. However, the coefficients on $PE_{[t-2,t]} \times Low$ are all insignificant.

Table 10 presents the results of the effects of PE buyouts on innovation outcomes when interacted with product market competition. Similar to what I obtain in Table 9, the coefficients on either $PE_{[t-2,t]} \times High$ or $PE_{[t-2,t]} \times Med$ are significant at either 5% or 1% level under all specifications while the coefficients on $PE_{[t-2,t]} \times Low$ are all insignificant. Taken together, the evidence obtained from Table 9 and 10 is largely consistent with “more focused target’s rivals” hypothesis.

6 Conclusions

This paper investigates the spillover effects of private equity (PE) buyouts on innovation of the targets’ public rivals. Given the critical role of innovation in economic growth, this study sheds light on the broader impacts of PE firms on industry and economy and provides a potential explanation as to why PE investments promote industry productivity and growth (Bernstein, Lerner, Sorensen, and Strömberg, 2017; Aldatmaz and Brown, 2016).

In spite of frequent negative publicity of PE firms hurting industry and economy, I find that, on average five years after PE buyouts, the targets’ industry rivals and direct competitors not only increase innovation output, measured by patent counts, but also improve innovation quality, measured by cite-weighted patent counts. In addition, by examining the effects of other types of acquisitions on innovation of the targets' peers, I find that this positive externality does not exist in general M&A deals but is unique to PE-backed deals.

However, establishing a causal relationship between PE buyouts and the target peers' innovation can be challenging due to inherent industry selection issues. To address this concern, I extract exogenous part of decision-making process regarding industry selection by analyzing PE firm's industry focus and experience. More specifically, for a given industry, I count how many PE firms actually focus on that industry and have successful past experience in that industry during a five-year window prior to the PE-backed deals in question as an instrument for the probability of subsequent buyout completion in the same industry. Using an instrumental variable approach, I then argue that the positive effect is causal.

Finally, I present evidence that PE buyouts affect industry innovation through increasing corporate focus of targets' rivals. Specially, I find that PE buyouts are associated with increased corporate focus of the targets' rivals and this positive association is unique to PE-backed deals. Given that PE-backed firms themselves become more focused after the buyout transaction, PE-backed firms force the target rivals to shift focus to the areas in which they are most experienced. And since conglomerates are shown to stifle innovation due to inefficiencies of internal capital market on allocating resources to multiple R&D divisions (Seru, 2014), forcing buyout target's rivals to become more focused is likely to be a channel through which PE buyouts increase the industry innovation.

Given that many firms only report one segment or two segments with one of them being financial services, it is hard to find a measure to capture the dynamic of internal capital market following PE investments for these firms even if many of them have multiple R&D divisions undertaking different research projects. Because of this difficulty of directly testing this channel, I conduct an indirect test based on product market competition, the results of which are consistent with the hypothesis that PE buyouts spur innovation of the target's rivals through changing the competitive environment of the target's industry by forcing the target's peers to become more focused.

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Figure 1. Relation between innovation intensity and PE investment frequency.
Innovation intensity is calculated by first computing the industry-year innovation intensity as the average number of patents for all patent-producing firms in each of Fama-French 49 industries in each year and then measure each industry's innovation intensity as its time-series mean during 1990–2009. Patent-producing firms are those that have at least one patent granted during the entire sample period. PE investment frequency is the unique rank, with ties broken arbitrarily, of the frequency of PE firms investing in each of Fama-French 49 industries during 1990–2009, and the unit of calculating the frequency is industry-year.

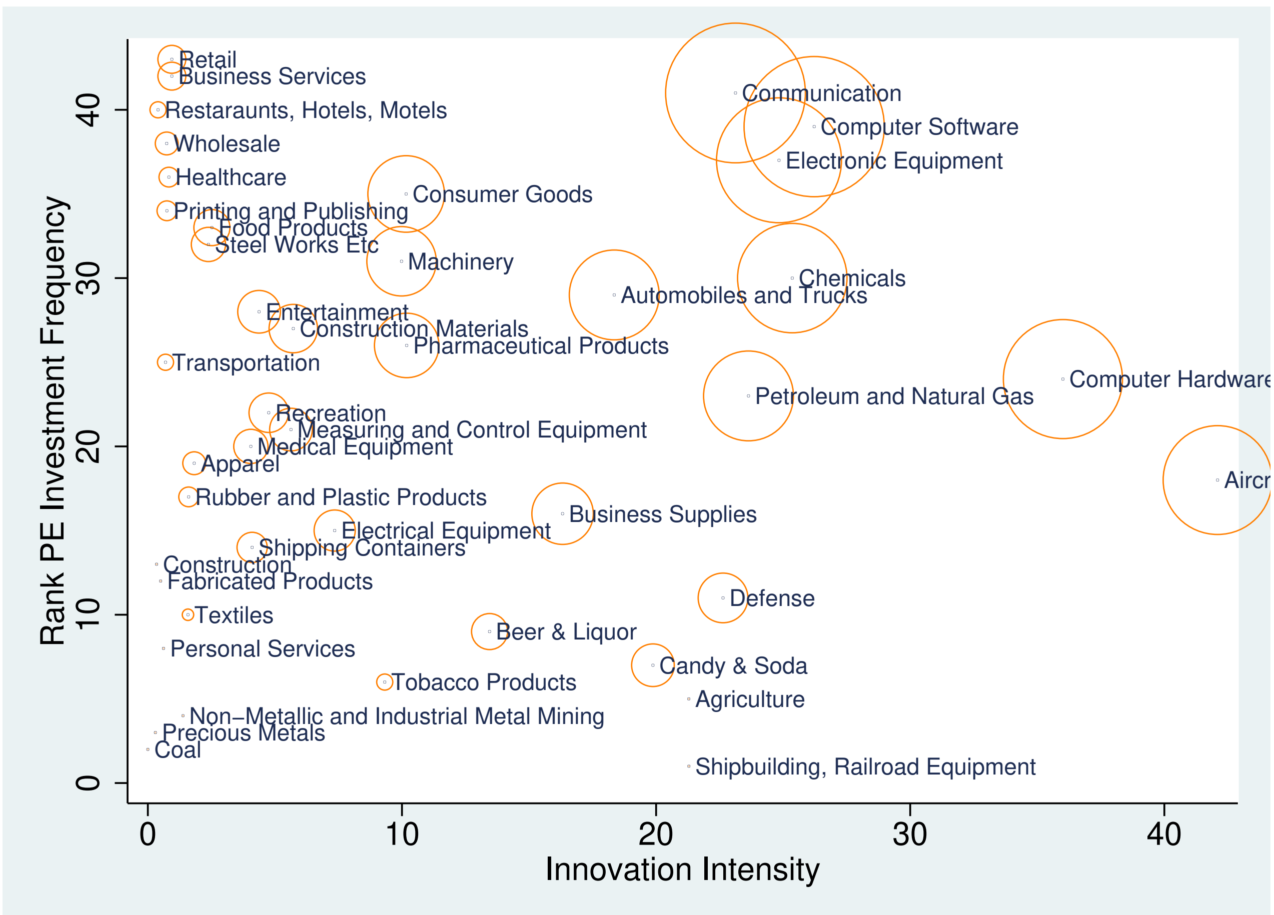


Figure 2. Dynamic Effects of PE Investments on Innovation.
The figure presents how PE investments around time *t* affect patent counts at time t. The estimates and 95% confidence intervals are taken from the following specification:

$$ln(Patent_{ijt}) = \alpha_0 + \sum_{n=-2}^{n=8} \gamma_n PE_{j,t-n} + \beta' X_{ijt} + \tau_{i(j)} + \mu_t + \varepsilon_{ijt}$$

. The dependent variable is natural logarithm of either patent counts or cite-weighted patent counts plus one for firm i in industry j in year t, in which a patent application was submitted. $PE_{j,t-n}$ is a dummy variable indicating if PE invested in 3-digit SIC industry j at time $t-n$. The specification is estimated using OLS and includes either firm fixed effects (τ_i) or 3-digit SIC industry fixed effects (τ_j), and year fixed effects (μ_t). Standard errors are clustered at the 3-digit SIC industry level. The estimates are reported in the Appendix.

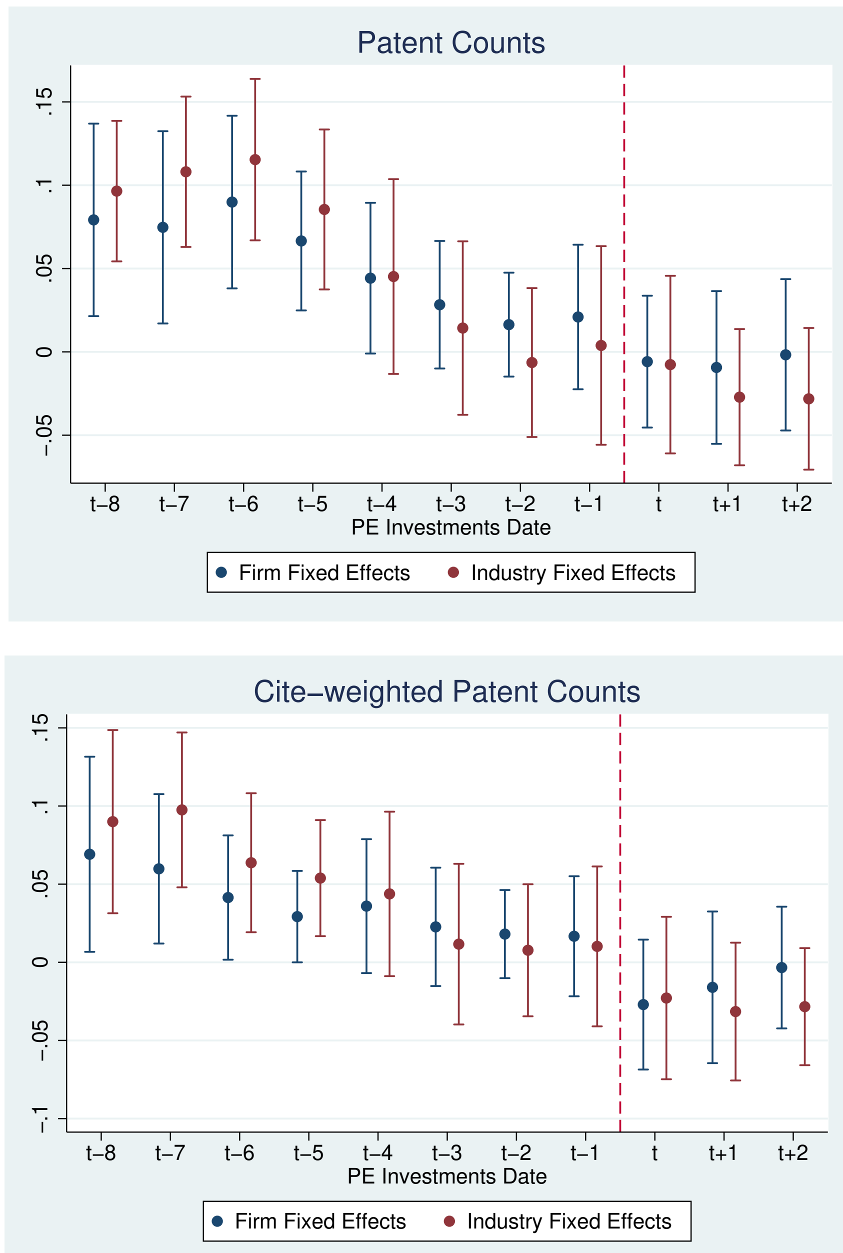


Figure 3. Relation between fraction of experienced deals and total deals.
This figure presents the relation between fraction of experienced deals and PE firms' total deals during the period of 1983 - 2009. 209 PE firms are divided into five groups according to their total deals. Experienced deals are defined based on the number of deals that are invested by same PE firm and whose targets are in the same industry. Green, red, and blue bars represent deals that are invested by same PE firms in same 2-digit SIC industry for more than twice, three times, and four times, respectively.

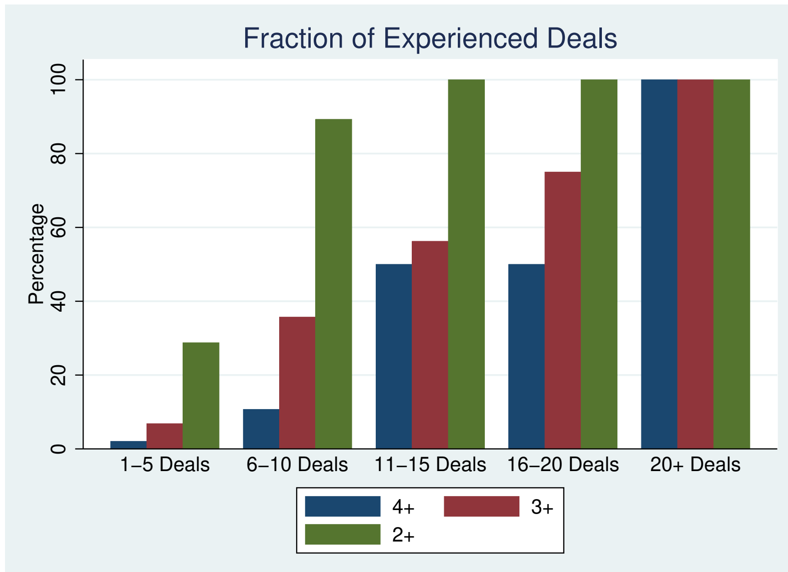


Figure 4.
This figure visualizes how the instrumental variable is constructed. A PE firm is considered a industry-experienced or industry-focused in a 2-digit SIC industry k at time t if it has completed at least two deals in industry k by time t. $Num\_Experienced_{kt}$ is defined as the number of industry-experienced PE firms that invested in a 2-digit SIC industry k in year t. W_{jt} is the ratio of the number of firms in a 3-digit SIC industry j to total firms of its corresponding 2-digit SIC industry in year t.

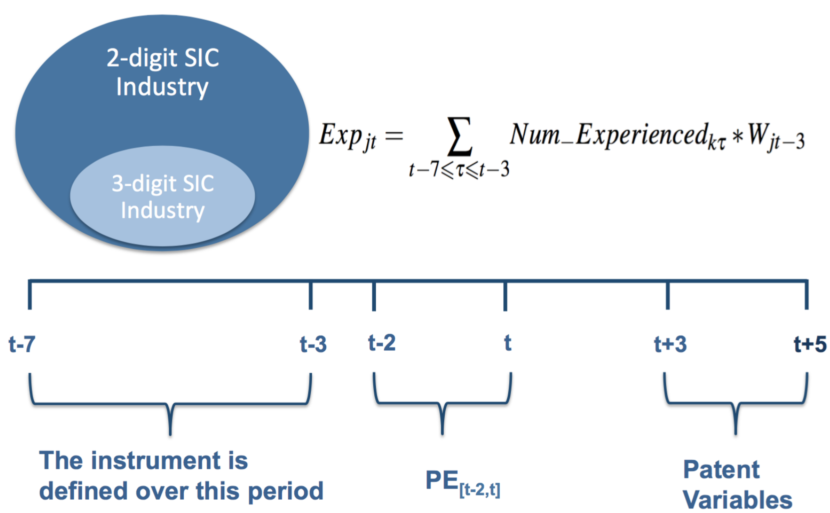


Figure 5. Relation between the instrumental variable (Exp_{jt}) and main variable ($PE_{[t-2,t]}$). This figure is based on the Logit Model estimation results from column (1) in Table 4 and shows how the instrumental variable affects the probability of subsequent PE buyout completion during a three-year window $[t-2,t]$. The definition of Exp_{jt} is in Section 4.2.

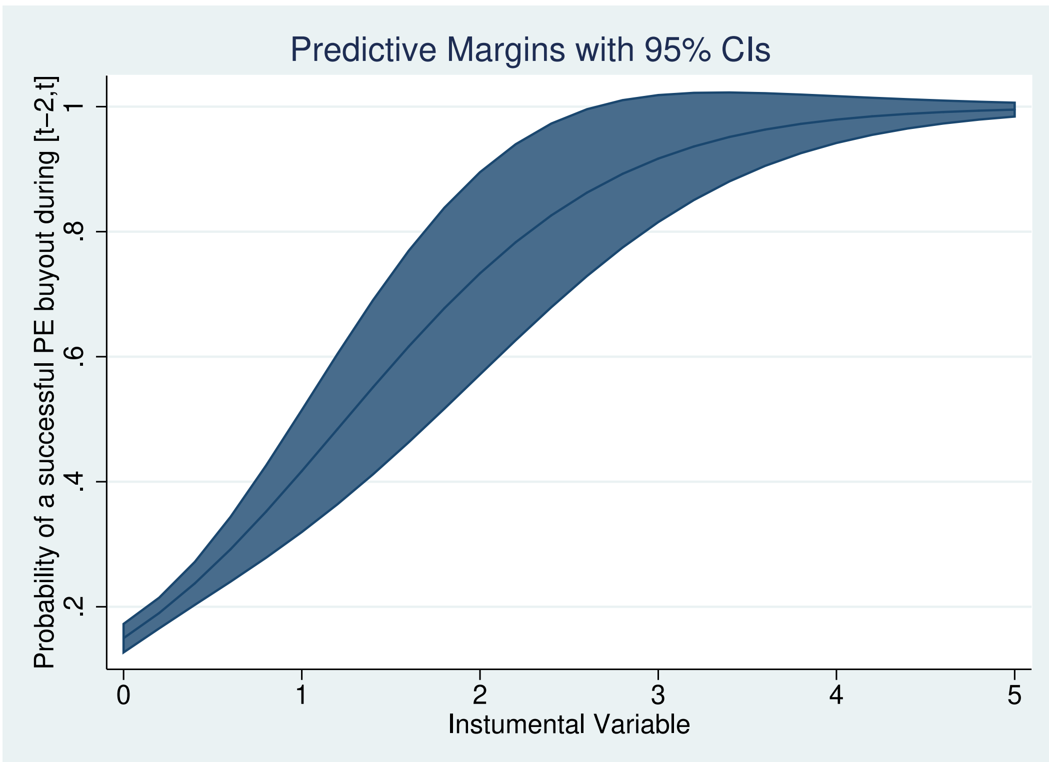
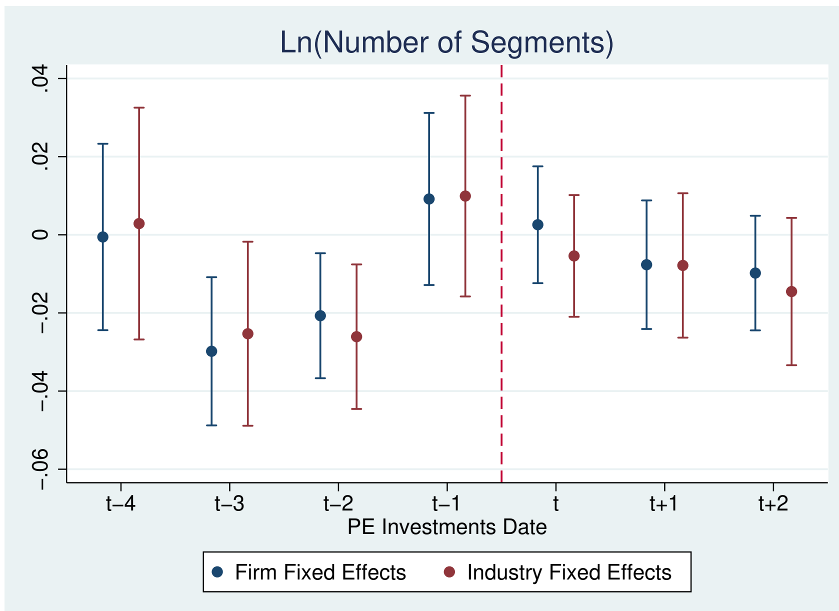


Figure 6: **Dynamic Effects of Both PE Investments and Other Acquisitions on Number of Business Segments.** The first graph presents how PE investments around time t affect number of business segments at time t, and the second graph presents how other types of acquisitions around time t affect number of business segments at time t.The estimates and 95% confidence intervals are taken from the following specification:

$$ln(Num\_Seg_{ijt}) = \alpha_0 + \sum_{n=-2}^{n=4} \gamma_n PE_{j,t-n}(non\text{-}PE_{j,t-n}) + \beta' X_{ijt} + \tau_{i(j)} + \mu_t + \varepsilon_{ijt}$$

The dependent variable is natural logarithm of number of business segments for firm i in industry j in year t. $PE_{j,t-n}$ is a dummy variable indicating if PE invested in 3-digit SIC industry j at time $t-n$. $non-PE_{j,t-n}$ is a dummy variable indicating if there are other types of acquisitions in 3-digit SIC industry j at time $t-n$.The specification is estimated using OLS and includes either firm fixed effects (τ_i) or 3-digit SIC industry fixed effects (τ_j), and year fixed effects (μ_t). Standard errors are clustered at the 3-digit SIC industry level. The estimates are reported in the Appendix.



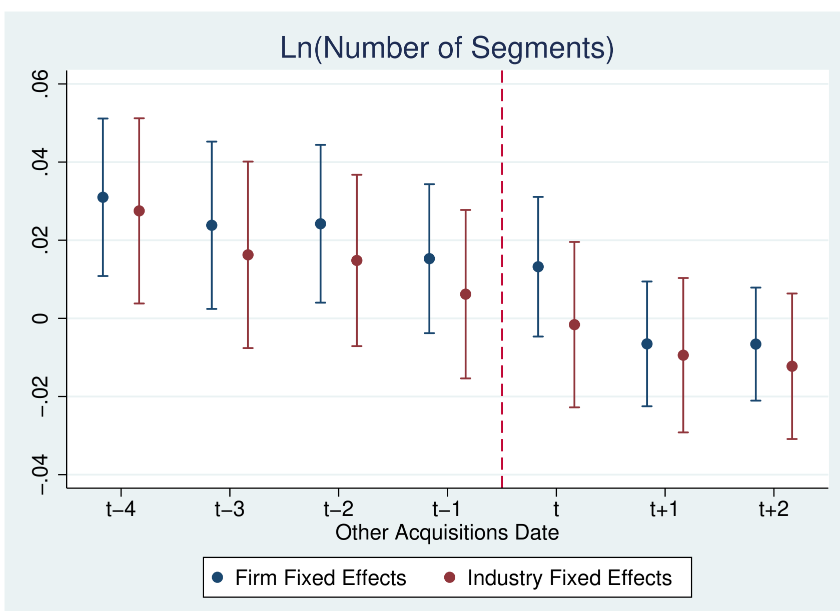


Table 1. **Deal distribution by year and industry.**
Panel A presents the number of successful PE buyout deals by year. Panel B presents the number of successful PE buyout deals by industry. PE-backed deals are completed between 1983 and 2009. A deal is a PE-backed if it satisfies: i) the acquirer or the acquirer's parent is a PE firm, ii) the shares owned after the transaction are greater than 50%, iii) the shares held by the acquirer before the transaction are less than 50%, iv) transaction value is greater than or equal to $100 million, and v) acquisitions take the form of merger (SDC deal form M), acquisition of majority interest (SDC deal form AM), or acquisition of assets (SDC deal form AA).

Panel A: Number of PE-backed deals by year

Year	N	Percent	Cum. Percent
1983	1	0.15	0.15
1984	5	0.73	0.87
1985	6	0.87	1.74
1986	8	1.16	2.90
1987	7	1.02	3.92
1988	9	1.31	5.22
1989	8	1.16	6.39
1990	5	0.73	7.11
1991	5	0.73	7.84
1992	4	0.58	8.42
1993	2	0.29	8.71
1994	10	1.45	10.16
1995	21	3.05	13.21
1996	16	2.32	15.53
1997	25	3.63	19.16
1998	31	4.50	23.66
1999	40	5.81	29.46
2000	31	4.50	33.96
2001	20	2.90	36.87
2002	24	3.48	40.35
2003	41	5.95	46.30
2004	63	9.14	55.44
2005	58	8.42	63.86
2006	73	10.60	74.46
2007	111	16.11	90.57
2008	42	6.10	96.66
2009	23	3.34	100.00
Total	689	100.00	100.00

Panel B: Number of PE-backed deals by target industry

FF 49 Industries	N	Percent	Cum. Percent
Agriculture	4	0.58	0.58
Food Products	15	2.18	2.76
Candy & Soda	2	0.29	3.05
Beer & Liquor	1	0.15	3.19
Tobacco Products	2	0.29	3.48
Recreation	8	1.16	4.64
Entertainment	13	1.89	6.53
Printing and Publishing	24	3.48	10.01
Consumer Goods	24	3.48	13.50
Apparel	9	1.31	14.80
Healthcare	37	5.37	20.17
Medical Equipment	12	1.74	21.92
Pharmaceutical Products	8	1.16	23.08
Chemicals	21	3.05	26.12
Rubber and Plastic Products	18	2.61	28.74
Textiles	5	0.73	29.46
Construction Materials	28	4.06	33.53
Construction	8	1.16	34.69
Steel Works Etc	18	2.61	37.30
Fabricated Products	6	0.87	38.17
Machinery	19	2.76	40.93
Electrical Equipment	5	0.73	41.65
Automobiles and Trucks	21	3.05	44.70
Aircraft	8	1.16	45.86
Shipbuilding, Railroad Equipment	1	0.15	46.01
Defense	2	0.29	46.30
Petroleum and Natural Gas	9	1.31	47.61
Communication	41	5.95	53.56
Personal Services	18	2.61	56.17
Business Services	67	9.72	65.89
Computer Hardware	9	1.31	67.20
Computer Software	36	5.22	72.42
Electronic Equipment	19	2.76	75.18
Measuring and Control Equipment	7	1.02	76.20
Business Supplies	15	2.18	78.37
Shipping Containers	6	0.87	79.25
Transportation	21	3.05	82.29
Wholesale	38	5.52	87.81
Retail	40	5.81	93.61
Restaraunts, Hotels, Motels	41	5.95	99.56
Almost Nothing	3	0.44	100.00
Total	689	100.00	100.00

Table 2. Summary Statistics

Panel A summarizes characteristics of the sample PE-backed Deals. Panel B presents characteristics of the firms and measures of corporate focus for patent-producing companies, which are defined as companies have at least one patent. PE-backed deals are completed between 1983 and 2009. Firms characteristics are based on sample period of 1990 through 2009. Transaction value is the size of the acquisition reported in millions of dollars. LBO is a dummy variable indicating if a PE-backed deal is a leverage buyout. Target public status is a dummy variable indicating if a target of PE-backed deal is a public company. PE_t is a dummy variable indicating if there are PE-backed deals completed in a 3-digit SIC industry in year t. $PE_{[t-2,t]}$ is a dummy variable indicating if there are PE-backed deals completed in a 3-digit SIC industry in a three-year window $[t-2,t]$. Patent Counts for each firm are based on the application year not the grant year and adjusted for truncation bias. Cite-weighted patent counts are patent counts scaled by scaled citations. Scaled citations is patent citation count divided by the average number of citations received by all patents that are granted in the same year and technology class. ln(Patent) is natural logarithm of Patent Counts plus one and ln(Cite) is natural logarithm of Cite-weighted Patent Counts plus one. Return on assets (ROA) is operating income before depreciation and amortization (Compustat item oibda) divided by total assets (Compustat item at). Size is the natural logarithm of total assets (Compustat item at). Market-to-book equals assets (Compustat item at) – common equity (ceq) + stock price (prcc_f) times common shares outstanding (csho) – deferred taxes (txdb), divided by total assets (at). Leverage equals debt in current liabilities (dlc) + long-term liabilities (dltt), divided by total assets. R&D is natural logarithm of R&D expenditure scaled by total asset plus one. Lerner Index is median value of markup (oibdp/sale) based on 3-digit SIC industry for a given year. Institutional Ownership is total percentage of a firms' equity held by institutional investors in a given year. Exp is number of industry-experienced PE firms scaled by number of firms in 3-digit SIC industry during the period of [t-7, t-3]. Single is a dummy variable and equal to one if the company only has one segment in a given year. Number of Segment is the number of segment for a company in a given year. Foc_R is a revenue-based Herfindahl index for a company in a given year. Foc_A is a asset-based Herfindahl index for a company in a given year.

Panel A: Characteristics of PE-backed deal

Variable	N	mean	sd	p25	p50	p75
Transaction value ($M)	689	641.06	1589.98	159.94	291.00	616.00
LBO	689	0.51	0.50	0.00	1.00	1.00
Target public status	689	0.30	0.46	0.00	0.00	1.00
PE_t	42230	0.26	0.44	0.00	0.00	1.00
$PE_{[t-2,t]}$	42230	0.44	0.50	0.00	0.00	1.00

Panel B: Firm Characteristics and Measures of Corporate Focus For Patent-Producing Firms

Variable	N	mean	sd	p25	p50	p75
Firm Characteristics						
Patent Counts	42230	15.17	108.11	0.00	0.00	4.00
Cite-weighted Patent Counts	42230	14.29	87.88	0.00	0.00	3.39
ln(Patent)	42230	0.97	1.36	0.00	0.00	1.61
ln(Cite)	42230	0.90	1.38	0.00	0.00	1.48
Size	42197	5.31	2.09	3.79	5.12	6.72
ROA	42085	0.04	0.25	0.01	0.11	0.17
Leverage	42032	0.18	0.21	0.01	0.10	0.28
Market-to-Book	40105	2.10	2.01	0.92	1.40	2.45
Institutional Ownership	41894	0.42	0.29	0.16	0.40	0.65
R&D	35824	0.09	0.11	0.01	0.05	0.12
Lerner Index	42230	0.01	0.27	0.05	0.08	0.11
Exp	42225	1.35	3.25	0.00	0.19	1.12
Measures of Focus						
Single	38903	0.65	0.48	0.00	1.00	1.00
Number of Segment	38903	1.89	1.52	1.00	1.00	3.00
Foc_R	19603	0.88	0.22	0.88	1.00	1.00
Foc_A	19603	0.88	0.22	0.86	1.00	1.00
Foc_P	20492	0.39	0.34	0.12	0.31	0.57

Table 3. Results of Baseline Specification

Table 2 presents results of baseline specification. Panel A shows the effects of both PE-backed deals and other non-PE-backed acquisitions on patent counts of target's peers, defined as firms in the same 3-digit SIC industry. Panel B shows the effects of both PE-backed deals and other non-PE-backed acquisitions on cite-weighted patent counts of target's peers, defined as firms in the same 3-digit SIC industry. For both Panels, column (1) through column (6) are estimated from OLS, and column(7) through column (9) are estimated from Poisson model. $PE_{[t-2,t]}$ is a dummy variable indicating if there are PE-backed deals completed in a given 3-digit industry during a three-year window $[t-2,t]$. *non-PE*$_{[t-2,t]}$ is a dummy variable indicating if there are other acquisitions completed in a given 3-digit industry during a three-year window $[t-2,t]$. Other variables are defined in Table 2. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

Panel A: Patent Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ln($Patent_{t+3}$)	ln($Patent_{t+3}$)	ln($Patent_{t+4}$)	ln($Patent_{t+4}$)	ln($Patent_{t+5}$)	ln($Patent_{t+5}$)	$Patent_{t+3}$	$Patent_{t+4}$	$Patent_{t+5}$
$PE_{[t-2,t]}$	0.044**		0.059***		0.052**		0.118***	0.186***	0.207***
	(0.019)		(0.019)		(0.024)		(0.042)	(0.046)	(0.052)
non-$PE_{[t-2,t]}$		-0.003		-0.000		0.007			
		(0.035)		(0.037)		(0.039)			
$Size_{t-2}$	0.110***	0.112***	0.086***	0.088***	0.051*	0.053*	0.300***	0.232***	0.168**
	(0.030)	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.088)	(0.080)	(0.077)
$Leverage_{t-2}$	-0.163**	-0.163**	-0.071	-0.070	-0.073	-0.072	-0.315	-0.256	-0.202
	(0.079)	(0.080)	(0.087)	(0.088)	(0.105)	(0.106)	(0.256)	(0.274)	(0.245)
ROA_{t-2}	0.032	0.032	0.010	0.009	-0.032	-0.033	0.138	0.126	-0.019
	(0.052)	(0.052)	(0.072)	(0.071)	(0.091)	(0.091)	(0.325)	(0.324)	(0.317)
Market/$Book_{t-2}$	0.016**	0.016**	0.016***	0.015***	0.009	0.009	0.003	-0.002	-0.000
	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.006)	(0.018)	(0.015)	(0.015)
R&D_{t-2}	0.361	0.369*	0.280	0.291	0.206	0.218	0.307	0.330	0.275
	(0.220)	(0.222)	(0.285)	(0.289)	(0.212)	(0.217)	(0.772)	(0.726)	(0.876)
Ins. $Ownership_{t-2}$	-0.112*	-0.113*	-0.180***	-0.183***	-0.172**	-0.175**	-0.004	0.118	0.198
	(0.066)	(0.067)	(0.069)	(0.069)	(0.075)	(0.076)	(0.254)	(0.234)	(0.204)
Lerner $Index_{t-2}$	0.203**	0.176**	0.293**	0.253**	0.176	0.139	1.008***	0.837***	0.420
	(0.084)	(0.074)	(0.128)	(0.114)	(0.170)	(0.160)	(0.338)	(0.320)	(0.309)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21229	21229	18774	18774	16518	16518	18757	16323	14216
R^2	0.092	0.092	0.103	0.102	0.111	0.110			

Panel B: Cite-Weighted Patent Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ln($Cite_{t+3}$)	ln($Cite_{t+3}$)	ln($Cite_{t+4}$)	ln($Cite_{t+4}$)	ln($Cite_{t+5}$)	ln($Cite_{t+5}$)	$Cite_{t+3}$	$Cite_{t+4}$	$Cite_{t+5}$
$PE_{[t-2,t]}$	0.059**		0.074***		0.041		0.110**	0.127***	0.111**
	(0.024)		(0.025)		(0.028)		(0.043)	(0.048)	(0.055)
non-$PE_{[t-2,t]}$		0.042		0.030		0.008			
		(0.040)		(0.043)		(0.044)			
$Size_{t-2}$	0.030	0.032	-0.014	-0.011	-0.058	-0.057	0.233***	0.145***	0.074
	(0.030)	(0.030)	(0.033)	(0.033)	(0.037)	(0.037)	(0.052)	(0.048)	(0.054)
$Leverage_{t-2}$	-0.111	-0.110	0.033	0.035	0.062	0.063	0.008	0.156	0.140
	(0.074)	(0.075)	(0.085)	(0.086)	(0.094)	(0.095)	(0.265)	(0.289)	(0.295)
ROA_{t-2}	0.079	0.078	0.183*	0.181*	0.108	0.107	0.028	0.242	0.063
	(0.086)	(0.085)	(0.093)	(0.092)	(0.117)	(0.117)	(0.260)	(0.272)	(0.307)
Market-to-$Book_{t-2}$	0.025***	0.025***	0.013	0.012	-0.004	-0.004	0.032***	0.013	-0.011
	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.011)	(0.010)	(0.012)
$R\&D_{t-2}$	0.108	0.120	0.294	0.309	0.140	0.149	0.779	0.667	0.266
	(0.343)	(0.346)	(0.321)	(0.326)	(0.293)	(0.296)	(0.592)	(0.519)	(0.557)
Ins. $Ownership_{t-2}$	-0.087	-0.090	-0.144	-0.147	-0.051	-0.053	0.338	0.441**	0.504**
	(0.078)	(0.078)	(0.091)	(0.092)	(0.101)	(0.101)	(0.220)	(0.215)	(0.207)
Lerner $Index_{t-2}$	0.317***	0.277***	0.468***	0.415***	0.345***	0.315***	0.739***	0.701**	0.571*
	(0.077)	(0.066)	(0.139)	(0.119)	(0.111)	(0.096)	(0.264)	(0.281)	(0.329)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21229	21229	18774	18774	16518	16518	17972	15609	13524
R^2	0.171	0.170	0.184	0.183	0.193	0.192			

Table 4. Relevance Condition and First Stage Results

Table 4 examines the relevance condition of instrumental variable. The analysis of unit in column (1) through (4) is industry-year (3-digit SIC code). Column(4) and (5) are estimated based on firm-years. Exp_t is the instrumental variable defined in equation (6). $PE_{[t-2,t]}$ is a dummy variable indicating if there are PE-backed deals completed in a given 3-digit industry during a three-year window $[t-2,t]$. *Shock*, following Harford (2005), measures industry economic shock. Other variables are defined in Table 2. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	Industry Level	Industry Level	Industry Level	Firm Level	First Stage
Dep. Variable: $PE_{[t-2,t]}$	Logit	Logit	Logit	Logit	2SLS
Exp_t	1.454***	1.134***	1.132***	0.669***	0.041***
	(0.215)	(0.211)	(0.230)	(0.239)	(0.008)
$Shock_{t-2}$		-0.383***	-0.752***	-0.736***	
		(0.120)	(0.227)	(0.238)	
Lerner $Index_{t-2}$		-0.432	-2.236***	-2.120***	-0.569***
		(0.653)	(0.393)	(0.433)	(0.158)
$Size_{t-2}$				0.009	0.031**
				(0.035)	(0.015)
$Leverage_{t-2}$				-0.108	0.027
				(0.220)	(0.043)
ROA_{t-2}				0.262	-0.003
				(0.297)	(0.045)
Market/$Book_{t-2}$				-0.004	0.001
				(0.019)	(0.005)
$R\&D_{t-2}$				1.593	0.153
				(1.152)	(0.121)
Ins. $Ownership_{t-2}$				-0.156	-0.037
				(0.184)	(0.040)
Industry fixed effects	No	No	Yes	No	No
Firm fixed effects	No	No	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	4630	4214	3917	29949	21229
R^2					0.214

Table 5. Placebo Test

This table presents a placebo test through OLS to assess the validity of exclusion restriction by examining the effects of the instrument on corporate innovation outcomes in 3-digit industries where there are no following PE buyout deals. Subsample only contains firms in 3-digit industries where there are no following PE buyout deals during $[t-2, t+2]$, given the instrument is defined over $[t-7, t-3]$. Other variables are defined in Table 2. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

Panel A: Patent Counts

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Patent_{t+3})$	$\ln(Patent_{t+3})$	$\ln(Patent_{t+4})$	$\ln(Patent_{t+4})$	$\ln(Patent_{t+5})$	$\ln(Patent_{t+5})$
	FullSample	Subsample	FullSample	Subsample	FullSample	Subsample
Exp_t	0.040***	0.071	0.048***	0.067*	0.049***	0.027
	(0.005)	(0.044)	(0.007)	(0.039)	(0.011)	(0.031)
$Size_{t-2}$	0.101***	0.164***	0.076***	0.137***	0.041	0.098**
	(0.027)	(0.035)	(0.027)	(0.033)	(0.027)	(0.038)
Lerner $Index_{t-2}$	0.216***	0.110	0.322***	0.246*	0.220*	0.064
	(0.064)	(0.076)	(0.093)	(0.140)	(0.133)	(0.167)
$Leverage_{t-2}$	-0.143*	-0.175	-0.039	-0.018	-0.038	0.001
	(0.077)	(0.124)	(0.081)	(0.119)	(0.096)	(0.122)
ROA_{t-2}	0.035	-0.013	0.014	0.053	-0.025	-0.038
	(0.049)	(0.093)	(0.065)	(0.129)	(0.086)	(0.131)
$Market/Book_{t-2}$	0.019***	0.028**	0.019***	0.025*	0.012**	0.007
	(0.007)	(0.013)	(0.005)	(0.013)	(0.006)	(0.011)
$R\&D_{t-2}$	0.329	1.141***	0.247	0.612	0.180	0.615
	(0.203)	(0.344)	(0.267)	(0.453)	(0.199)	(0.423)
Ins. $Ownership_{t-2}$	-0.111	-0.070	-0.177**	-0.078	-0.165**	-0.014
	(0.068)	(0.095)	(0.069)	(0.109)	(0.073)	(0.116)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	21229	8801	18774	8140	16518	7495
R^2	0.097	0.086	0.108	0.093	0.115	0.112

Panel B: Cite-weighted Patent Counts

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Cite$_{t+3}$)	ln(Cite$_{t+3}$)	ln(Cite$_{t+4}$)	ln(Cite$_{t+4}$)	ln(Cite$_{t+5}$)	ln(Cite$_{t+5}$)
	FullSample	Subsample	FullSample	Subsample	FullSample	Subsample
Exp_t	0.015***	0.078	0.020**	0.060	0.018	0.015
	(0.005)	(0.054)	(0.008)	(0.038)	(0.012)	(0.028)
Size$_{t-2}$	0.028	0.142***	-0.016	0.106**	-0.061	0.062
	(0.029)	(0.046)	(0.033)	(0.050)	(0.038)	(0.056)
Lerner Index$_{t-2}$	0.295***	0.170*	0.446***	0.308*	0.347***	0.216
	(0.063)	(0.100)	(0.116)	(0.186)	(0.096)	(0.146)
Leverage$_{t-2}$	-0.103	-0.183	0.047	0.059	0.075	0.033
	(0.073)	(0.125)	(0.084)	(0.115)	(0.094)	(0.115)
ROA_{t-2}	0.080	-0.026	0.184**	0.142	0.110	-0.003
	(0.084)	(0.111)	(0.091)	(0.160)	(0.115)	(0.151)
Market/Book_{t-2}	0.026***	0.021*	0.014*	0.012	-0.003	-0.014
	(0.009)	(0.012)	(0.008)	(0.012)	(0.007)	(0.012)
R&D_{t-2}	0.104	1.026**	0.290	0.503	0.135	0.698
	(0.338)	(0.425)	(0.317)	(0.690)	(0.288)	(0.527)
Ins. Ownership_{t-2}	-0.089	-0.073	-0.144	-0.064	-0.050	0.037
	(0.078)	(0.120)	(0.092)	(0.124)	(0.101)	(0.118)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	21229	8801	18774	8140	16518	7495
R^2	0.171	0.115	0.183	0.130	0.193	0.150

Table 6. 2SLS Results

This table reports 2SLS estimation results. $PE_{[t-2,t]}$ is the predicted value from equation (7). Other variables are defined in Table 2. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Patent$_{t+3}$)	ln(Patent$_{t+4}$)	ln(Patent$_{t+5}$)	ln(Cite$_{t+3}$)	ln(Cite$_{t+4}$)	ln(Cite$_{t+5}$)
$PE_{[t-2,t]}$	0.971***	1.009***	0.921***	0.360***	0.416***	0.348*
	(0.216)	(0.218)	(0.261)	(0.127)	(0.154)	(0.209)
Size$_{t-2}$	0.071**	0.047*	0.017	0.017	-0.027	-0.070*
	(0.030)	(0.025)	(0.023)	(0.028)	(0.031)	(0.038)
Lerner Index$_{t-2}$	0.768***	0.939***	0.796**	0.500***	0.701***	0.564**
	(0.215)	(0.307)	(0.366)	(0.130)	(0.219)	(0.222)
Leverage$_{t-2}$	-0.169**	-0.085	-0.081	-0.113	0.028	0.059
	(0.084)	(0.084)	(0.100)	(0.073)	(0.082)	(0.091)
ROA$_{t-2}$	0.039	0.024	-0.006	0.082	0.188*	0.118
	(0.078)	(0.092)	(0.109)	(0.091)	(0.098)	(0.118)
Market/Book$_{t-2}$	0.018***	0.020***	0.015**	0.026***	0.014**	-0.002
	(0.005)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)
R&D$_{t-2}$	0.181	0.094	0.012	0.049	0.227	0.071
	(0.192)	(0.218)	(0.172)	(0.307)	(0.279)	(0.247)
Ins. Ownership$_{t-2}$	-0.075	-0.143*	-0.125*	-0.075	-0.130	-0.035
	(0.075)	(0.078)	(0.070)	(0.077)	(0.090)	(0.101)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	21229	18774	16518	21229	18774	16518

Table 7. More Subsequent Acquisitions in the Target Industry

Table 7 presents the effects, estimated by Logit model, of both of PE-backed and non-PE-backed deals on the probability of following acquisitions in the target industry in one year, two years, and three years, respectively. *Acquired* $_{t+1}$, *Acquired* $_{t+2}$, and *Acquired* $_{t+3}$ are dummy variables indicate if a company is successfully acquired in year $t+1$, $t+2$, and $t+3$, respectively. *Shock*, following Harford (2005), measures industry economic shock. Other variables are defined in Table 2. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	(1) Acquired $_{t+1}$	(2) Acquired $_{t+1}$	(3) Acquired $_{t+2}$	(4) Acquired $_{t+2}$	(5) Acquired $_{t+3}$	(6) Acquired $_{t+3}$
$\text{PE}_{[t-2,t]}$	0.260***		0.291***		0.293***	
	(0.095)		(0.104)		(0.105)	
$\text{non-PE}_{[t-2,t]}$		0.437***		0.374***		0.334***
		(0.126)		(0.122)		(0.117)
Shock_{t-2}	0.071*	0.081**	0.058	0.063	-0.015	-0.008
	(0.037)	(0.039)	(0.052)	(0.054)	(0.083)	(0.086)
$\text{Lerner Index}_{t-2}$	0.041	-0.023	0.012	-0.079	-0.051	-0.139
	(0.116)	(0.100)	(0.129)	(0.120)	(0.123)	(0.116)
Size_{t-2}	0.112***	0.112***	0.104***	0.105***	0.101***	0.101***
	(0.020)	(0.020)	(0.023)	(0.023)	(0.023)	(0.023)
Market/Book_{t-2}	0.042**	0.044***	0.034	0.037*	0.023	0.025
	(0.016)	(0.017)	(0.022)	(0.022)	(0.027)	(0.027)
Leverage_{t-2}	0.112	0.115	0.035	0.029	-0.009	-0.016
	(0.203)	(0.206)	(0.186)	(0.191)	(0.208)	(0.213)
ROA_{t-2}	0.411***	0.403***	0.486***	0.474***	0.384**	0.373*
	(0.145)	(0.149)	(0.152)	(0.157)	(0.188)	(0.192)
$\text{Ins. Ownership}_{t-2}$	0.697***	0.699***	0.684***	0.681***	0.589***	0.586***
	(0.139)	(0.144)	(0.186)	(0.188)	(0.185)	(0.187)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	56146	56146	48815	48815	42405	42405

Table 8. Direct Competitors

Table 8 presents results of the impacts on the targets' direct competitors through OLS. $PE_{[t-2,t]}$ is a dummy variable indicating if one of a firm's competitors was bought out by a PE firm during a three-year window $[t-2,t]$. Other variables are defined in Table 2. Robust standard errors are clustered at firm level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Patent$_{t+3}$)	ln(Patent$_{t+4}$)	ln(Patent$_{t+5}$)	ln(Cite$_{t+3}$)	ln(Cite$_{t+4}$)	ln(Cite$_{t+5}$)
$PE_{[t-2,t]}$	0.197***	0.182**	0.243**	0.177**	0.147*	0.080
	(0.074)	(0.090)	(0.102)	(0.076)	(0.089)	(0.104)
Size$_{t-2}$	0.108***	0.082***	0.048*	0.032	-0.013	-0.057**
	(0.023)	(0.024)	(0.025)	(0.022)	(0.024)	(0.027)
Leverage$_{t-2}$	-0.159**	-0.056	-0.073	-0.115*	0.036	0.049
	(0.067)	(0.070)	(0.076)	(0.068)	(0.074)	(0.080)
ROA$_{t-2}$	0.040	0.023	-0.024	0.082	0.184***	0.114
	(0.057)	(0.062)	(0.067)	(0.064)	(0.071)	(0.080)
Market-to-Book$_{t-2}$	0.016***	0.015***	0.008	0.025***	0.012**	-0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
R&D$_{t-2}$	0.402**	0.386**	0.253	0.204	0.409**	0.194
	(0.171)	(0.183)	(0.195)	(0.188)	(0.208)	(0.214)
Lerner Index$_{t-2}$	0.162**	0.250***	0.116	0.277***	0.422***	0.289***
	(0.073)	(0.091)	(0.106)	(0.089)	(0.114)	(0.111)
Institutional Ownership_{t-2}	-0.101	-0.159**	-0.149*	-0.096	-0.126	-0.039
	(0.066)	(0.074)	(0.079)	(0.072)	(0.082)	(0.087)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	21080	18644	16403	21080	18644	16403
R^2	0.094	0.104	0.113	0.170	0.182	0.191

Table 9. Increased Corporate Focus of Buyout Target's Rivals

This table presents the effects, estimated by OLS, of both PE-backed and non-PE-backed deals on the target rivals' corporate focus. Panel A shows the effects on asset-based Herfindahl index and Panel B shows the effects on revenue-based Herfindahl index. Foc_R is a revenue-based Herfindahl index for a company in a given year. Foc_A is a asset-based Herfindahl index for a company in a given year. All other variables are defined in Table 2. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

Panel A: Asset-based Herfindahl Index

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Foc\_A_{t+3})$	$\ln(Foc\_A_{t+3})$	$\ln(Foc\_A_{t+4})$	$\ln(Foc\_A_{t+4})$	$\ln(Foc\_A_{t+5})$	$\ln(Foc\_A_{t+5})$
$PE_{[t-2,t]}$	0.027***		0.026**		0.040***	
	(0.010)		(0.013)		(0.015)	
non-$PE_{[t-2,t]}$		0.006		-0.002		0.002
		(0.012)		(0.015)		(0.019)
$Size_{t-2}$	-0.039***	-0.038***	-0.041***	-0.040***	-0.038**	-0.036**
	(0.011)	(0.011)	(0.013)	(0.013)	(0.015)	(0.015)
$Leverage_{t-2}$	0.020	0.018	0.045	0.043	0.069*	0.062*
	(0.023)	(0.024)	(0.032)	(0.032)	(0.037)	(0.037)
$Market/Book_{t-2}$	0.001	0.001	0.003	0.003	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
ROA_{t-2}	0.019	0.020	0.020	0.021	0.040	0.041
	(0.017)	(0.016)	(0.024)	(0.024)	(0.033)	(0.033)
Lerner $Index_{t-2}$	0.032	-0.002	-0.032	-0.057	-0.143***	-0.161***
	(0.027)	(0.027)	(0.047)	(0.048)	(0.052)	(0.050)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	8957	8957	7119	7119	5430	5430
R^2	0.037	0.035	0.039	0.038	0.045	0.042

Panel B: Revenue-based Herfindahl Index

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(\text{Fo}c\_\text{R}_{t+3})$	$\ln(\text{Fo}c\_\text{R}_{t+3})$	$\ln(\text{Fo}c\_\text{R}_{t+4})$	$\ln(\text{Fo}c\_\text{R}_{t+4})$	$\ln(\text{Fo}c\_\text{R}_{t+5})$	$\ln(\text{Fo}c\_\text{R}_{t+5})$
$\text{P}E_{[t-2,t]}$	0.026***		0.025**		0.043***	
	(0.010)		(0.012)		(0.014)	
non-$\text{P}E_{[t-2,t]}$		-0.002		-0.003		0.005
		(0.012)		(0.013)		(0.018)
Size_{t-2}	-0.041***	-0.040***	-0.041***	-0.040***	-0.033**	-0.031**
	(0.010)	(0.010)	(0.012)	(0.012)	(0.014)	(0.015)
Leverage_{t-2}	0.033	0.031	0.065*	0.063*	0.083**	0.076**
	(0.023)	(0.024)	(0.034)	(0.034)	(0.036)	(0.037)
Market/Book_{t-2}	0.000	0.000	0.002	0.002	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ROA_{t-2}	0.009	0.010	-0.001	-0.001	-0.010	-0.010
	(0.018)	(0.018)	(0.022)	(0.022)	(0.034)	(0.035)
$\text{Lerner Index}_{t-2}$	0.033	0.001	-0.021	-0.045	-0.163***	-0.183***
	(0.028)	(0.027)	(0.043)	(0.045)	(0.059)	(0.055)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	8957	8957	7119	7119	5430	5430
R^2	0.043	0.041	0.044	0.043	0.053	0.050

Table 10. Interaction Between Product Market Competition and Corporate Focus

This table presents the effects of PE buyouts, estimated by OLS, on corporate focus of the target's rivals when interacted with product market competition. Num_Seg is the number of segments for a company in a given year. Foc_R is a revenue-based Herfindahl index for a company in a given year. Foc_A is a asset-based Herfindahl index for a company in a given year. Lerner Index is used as a proxy for product market competition. The lower value of the Lerner index implies more intense product market competition. High, Med, and Low indicate the level of product market competition for each 3-digit SIC industry and equals one if the Lerner Index lies in the bottom, medium, and top tercile, respectively, of its empirical distribution. Other variables are defined in Table 2. In addition, High, Med, and Low are time-invariant and thus absorbed by firm fixed effects. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(Num\_Seg_{t+2})$	$\ln(Num\_Seg_{t+3})$	$\ln(Foc\_A_{t+3})$	$\ln(Foc\_A_{t+4})$	$\ln(Foc\_A_{t+5})$	$\ln(Foc\_R_{t+3})$	$\ln(Foc\_R_{t+4})$	$\ln(Foc\_R_{t+5})$
$PE_{[t-2,t]}$*High Com.	-0.050***	-0.052***	0.025	0.030	0.084***	0.018	0.023	0.085***
	(0.019)	(0.016)	(0.017)	(0.018)	(0.024)	(0.016)	(0.018)	(0.020)
$PE_{[t-2,t]}$*Med Com.	-0.038**	-0.050**	0.042***	0.034**	0.032	0.042***	0.036**	0.038
	(0.015)	(0.020)	(0.015)	(0.017)	(0.024)	(0.015)	(0.017)	(0.024)
$PE_{[t-2,t]}$*Low Com.	0.022	0.031	-0.006	0.013	0.023	-0.000	0.014	0.025
	(0.022)	(0.026)	(0.018)	(0.020)	(0.022)	(0.016)	(0.019)	(0.023)
$Size_{t-2}$	0.058***	0.051***	-0.039***	-0.041***	-0.038**	-0.041***	-0.040***	-0.033**
	(0.014)	(0.013)	(0.010)	(0.013)	(0.015)	(0.010)	(0.012)	(0.015)
$Leverage_{t-2}$	-0.025	-0.016	0.021	0.046	0.067*	0.034	0.066*	0.082**
	(0.035)	(0.038)	(0.023)	(0.032)	(0.037)	(0.023)	(0.035)	(0.035)
$Market/Book_{t-2}$	0.004*	0.002	0.001	0.003	0.002	0.000	0.002	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
ROA_{t-2}	-0.021	-0.014	0.020	0.019	0.037	0.010	-0.002	-0.014
	(0.023)	(0.026)	(0.017)	(0.024)	(0.033)	(0.019)	(0.022)	(0.034)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	25853	22836	8957	7119	5430	8957	7119	5430
R^2	0.566	0.552	0.038	0.039	0.045	0.044	0.045	0.052

Table 11. Interaction Between Product Market Competition and Innovation

This table presents the effects of PE buyouts, estimated by OLS, on innovation outcomes of the target's rivals when interacted with product market competition. Lerner Index is used as a proxy for product market competition. The lower value of the Lerner index implies more intense product market competition. High, Med, and Low indicate the level of product market competition for each 3-digit SIC industry and equals one if the Lerner Index lies in the bottom, medium, and top tercile, respectively, of its empirical distribution. Other variables are defined in Table 2. In addition, High, Med, and Low are time-invariant and thus absorbed by firm fixed effects. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	(1) ln($Patent_{t+3}$)	(2) ln($Patent_{t+4}$)	(3) ln($Patent_{t+5}$)	(4) ln($Cite_{t+3}$)	(5) ln($Cite_{t+4}$)	(6) ln($Cite_{t+5}$)
$PE_{[t-2,t]} \times$High	0.040**	0.047**	0.057**	0.040**	0.022	-0.020
	(0.019)	(0.022)	(0.022)	(0.019)	(0.020)	(0.035)
$PE_{[t-2,t]} \times$Med	0.032	0.048	0.051	0.054*	0.098***	0.071**
	(0.035)	(0.033)	(0.030)	(0.030)	(0.023)	(0.031)
$PE_{[t-2,t]} \times$Low	0.039	0.061	0.068	0.059	0.075	0.069
	(0.058)	(0.067)	(0.073)	(0.052)	(0.058)	(0.063)
$Size_{t-2}$	0.107***	0.082***	0.050	0.026	-0.017	-0.060
	(0.030)	(0.031)	(0.031)	(0.031)	(0.034)	(0.039)
$Leverage_{t-2}$	-0.167**	-0.074	-0.074	-0.116	0.032	0.060
	(0.079)	(0.086)	(0.105)	(0.076)	(0.085)	(0.094)
ROA_{t-2}	0.036	0.014	-0.031	0.085	0.190*	0.109
	(0.053)	(0.073)	(0.093)	(0.092)	(0.099)	(0.123)
$Market/Book_{t-2}$	0.016**	0.016***	0.009	0.025***	0.013	-0.004
	(0.007)	(0.005)	(0.006)	(0.009)	(0.008)	(0.007)
$R\&D_{t-2}$	0.344	0.254	0.195	0.087	0.268	0.129
	(0.224)	(0.307)	(0.229)	(0.364)	(0.360)	(0.323)
Ins. $Ownership_{t-2}$	-0.109	-0.175**	-0.169**	-0.084	-0.139	-0.048
	(0.067)	(0.069)	(0.075)	(0.079)	(0.091)	(0.102)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	21229	18774	16518	21229	18774	16518
R^2	0.092	0.102	0.110	0.170	0.182	0.192

Table 12. Robustness Checks

Table 11 conducts various robustness tests. Column (1) and (2) in show the results without companies subsequently becoming acquirers. Column (3) and (4) exclude Computer Hardware and Aircraft industry (based on FF-49 classification). Column (5) and (6) show the effect of PE buyouts whose targets are private companies. In column (7) and (8), buyout target's peers are defined based on 4-digit SIC industry. Other variables are defined in Table 2. For all specifications, robust standard errors are clustered at 3-digit SIC level and reported in in parentheses. *, *, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Patent$_{t+3}$)	ln(Cite$_{t+3}$)	ln(Patent$_{t+3}$)	ln(Cite$_{t+3}$)	ln(Patent$_{t+3}$)	ln(Cite$_{t+3}$)	ln(Patent$_{t+3}$)	ln(Cite$_{t+3}$)
PE$_{[t-2,t]}$	0.039**	0.049**	0.058***	0.075***	0.050***	0.065**	0.078***	0.103***
	(0.019)	(0.021)	(0.017)	(0.025)	(0.017)	(0.027)	(0.028)	(0.041)
Lerner Index$_{t-2}$	0.167*	0.272***	0.214**	0.466***	0.200**	0.312***	0.233**	0.172***
	(0.088)	(0.084)	(0.086)	(0.141)	(0.085)	(0.077)	(0.088)	(0.064)
Size$_{t-2}$	0.059**	0.009	0.111***	-0.014	0.110***	0.030	0.069**	0.019
	(0.026)	(0.030)	(0.033)	(0.033)	(0.030)	(0.030)	(0.030)	(0.020)
Leverage$_{t-2}$	-0.114	-0.101	-0.162*	0.043	-0.164**	-0.112	0.104	-0.201
	(0.071)	(0.073)	(0.084)	(0.085)	(0.080)	(0.075)	(0.051)	(0.103)
ROA$_{t-2}$	0.047	0.022	0.037	0.181*	0.030	0.077	0.037	0.012
	(0.048)	(0.073)	(0.058)	(0.093)	(0.053)	(0.087)	(0.043)	(0.051)
Market/Book$_{t-2}$	0.016*	0.021**	0.013**	0.013*	0.016**	0.024***	0.026**	0.038**
	(0.008)	(0.008)	(0.006)	(0.008)	(0.007)	(0.009)	(0.008)	(0.018)
R&D$_{t-2}$	0.201	-0.125	0.365	0.286	0.362	0.109	0.401**	0.225**
	(0.185)	(0.303)	(0.230)	(0.321)	(0.221)	(0.345)	(0.185)	(0.103)
Ins. Ownership$_{t-2}$	-0.118	-0.175**	-0.097	-0.147	-0.111*	-0.087	-0.108	-0.245**
	(0.074)	(0.071)	(0.069)	(0.092)	(0.066)	(0.078)	(0.074)	(0.071)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17666	17666	19919	18594	21229	21229	17666	17666
R^2	0.070	0.105	0.096	0.183	0.092	0.171	0.070	0.105