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*Diversified Institutional Ownership and Firm Innovation*

BY

*Yen-Lin Huang*

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY  
ROBINSON COLLEGE OF BUSINESS  
2022

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2022

### **ACCEPTANCE**

This dissertation was prepared under the direction of the *Yen-Lin Huang* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

Richard Phillips, Dean

### **DISSERTATION COMMITTEE**

**Vikas Agarwal (Chair)**

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ABSTRACT

*Diversified Institutional Ownership and Firm Innovation*

BY

*Yen-Lin Huang*

*December 8, 2022*

Committee Chair: *Vikas Agarwal*

Major Academic Unit: *J. Mack Robinson College of Business*

In this paper, I investigate the impact of diversified institutional ownership on firm innovation. I find that innovation productivity improves along with an increase in ownership by diversified institutions. This result is supported by a natural experiment design based on financial institution mergers. The results are consistent with the hypothesis that information complementarity drives the higher innovation productivity of firms held by institutional investors with diversified portfolios.

# **Diversified Institutional Ownership and Firm Innovation**

**Yen-Lin Huang**

## **Abstract**

In this paper, I investigate the impact of diversified institutional ownership on firm innovation. I find that innovation productivity improves along with an increase in ownership by diversified institutions. This result is supported by a natural experiment design based on financial institution mergers. The results are consistent with the hypothesis that information complementarity drives the higher innovation productivity of firms held by institutional investors with diversified portfolios.

## **1. Introduction**

It is well recognized in the finance literature that institutional investors have an important impact on a firm's decisions. Given their significant positions and great resources, institutional investors have both the ability and incentive to monitor the firms in their holdings and ensure that the managers behave in the best interest of shareholders. The literature also documents that these institutional block holders have different identities and characteristics, which have different implications for the governance they provide. For instance, Bushee (1998, 2001) finds that transient investors with higher turnover rates are associated with more myopic behavior for the firms in their portfolios, while Chhaochharia and Grinstein (2009) find better monitoring of CEO compensation for firms held by external institutional investors.

One of the institutional investor characteristics that can potentially affect firm decisions is portfolio diversification across different sectors. Figure 1 shows institutional investors' Herfindahl-Hirschman Index (HHI) trends since the 1980s; as the graph shows, HHI has increased significantly in recent years, indicating a trend toward a more concentrated portfolio for institutional investors. It is therefore important to understand whether institutional investors' portfolio diversification significantly affects the behaviors of the firms they invest in.

In this paper, I investigate how the portfolio diversification of institutional investors affects the innovation decisions of the firms they hold. I focus on innovation for two reasons: first, innovation is an important investment decision for the company that may create large economic benefits and competitive advantages, and second, it is an important

element that fuels overall economic growth (Solow, 1957). However, productive innovation requires long-term commitment. Without proper governance, managers may underinvest in innovation and focus more on meeting short-term goals or boosting near-term stock price. Consistent with this conjecture, Atanasov (2013) finds that when governance is negatively affected by anti-takeover laws, both quantity and quality of firm innovation output decline.<sup>1</sup>

Institutional investor diversification may have an impact on innovation for several reasons. First, if one believes that institutional investors' governance can help cultivate innovation, and that investor attention is limited, holding many firms from different industries may dilute the average attention that each industry/firm in the portfolio receives. It could thus affect the institutions' ability to monitor all portfolio firms and reduce the innovation outputs. The notion that investors may have limited attention is supported by theoretical and empirical evidence. For example, Kempf et al. (2017) and Liu et al. (2019) show that monitoring from institutional investors is negatively affected when they are distracted by exogenous events in other industries. Meanwhile, it is also arguable that the attention of institutional investors is not necessarily helpful for innovation development. Manso (2011) shows that the optimal incentive scheme to encourage innovation is to tolerate short-term failure and reward long-term success. If one believes institutional investors tend to focus on short-term profitability rather than long-term value, less intervention from institutional investors may actually allow the board to focus on long-term investments, including innovation.

Diversified institutional investors can also help with innovation productivity through information synergy and complementarities. Kini et al. (2009) find that international analysts with diverse portfolios across different sectors have access to varied information and can improve their forecasts due to information complementarities. Similarly, diversified institutional investors that hold firms across different industries can gather different information that may improve their advice and preference on innovation investments. For example, such an informed investor can borrow ideas from different

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<sup>1</sup> Karpoff and Wittry (2018) critiqued the usage of the Business Combination Laws as the only exogenous shock on governance, but when using the Poison Pill Laws instead, they reached the same conclusion: that governance negatively affects innovation.

industries to stimulate innovation or improve the innovation efficiency of a firm.

As this discussion shows, studying how institutional investor diversification affects innovation is an interesting empirical question. To investigate it, I first estimate a panel regression of innovation on ownership and investor diversification and confirm the finding in the prior literature that institutional ownership has positive and significant effects on innovation inputs and output quality. Moreover, controlling for overall ownership, I find that higher ownership from diversified investors further strengthens the effect. Given similar overall ownership, firms held by more diversified institutions invest more in innovation activities and are significantly more productive in terms of patent values and citations.

However, the results from panel regressions are subject to endogeneity issues and cannot be used to draw a causal conclusion. For example, it could be the case that diversified institutions are more likely to invest in firms with more productive innovation activities. Alternatively, some unobservable variables might exist that correlate with both investor diversification and innovation. To address these potential endogeneity issues, I exploit a natural experiment based on the merger of financial institutions to identify plausible exogenous changes in *diversified ownership*—which I define here as the fraction of outstanding shares owned by diversified institutions. Intuitively, the degree of portfolio diversification for the merged institutions is likely to be higher than before the merger. If two institutions do not invest in the exact same industries, then combining their portfolios will expand the number of sectors in the new portfolio and increase the portfolio diversification. Importantly, because decisions about institutional mergers are unlikely to be influenced by the individual firms in the institution's portfolio, the increase in investor diversification can be considered exogenous at the firm level. In my natural experiment, the treated firms include all firms that are held by either of the merging parties (but not both) before the merger announcement, while the control firms are not held by either of the merging institutions. I did not include firms held by both institutions before the merger in the treated group because the ownership concentration for such firms will increase after the merger, which can confound the effect of diversified institutional ownership that I want to identify. To validate this design, I investigate the changes in diversified institutional ownership before and after the mergers and find that the treated firms experience a larger



increase in diversified institutional ownership than the control firms.

Based on the experiment design, I then test how the mergers impact innovation for the treated and control firms. I find that the treated firms acquire more patents after the mergers. These patents also have more citations and higher values, as captured by the market reaction after they are granted. I also explore the effects on R&D investment efficiency, which is captured by innovation output measures divided by R&D expense or R&D capital. I find that after the mergers, R&D expenditures (as a percentage of total sales) do not show different patterns between the treated and control firms, but investment efficiency significantly improves more for the treated firms. Moreover, the farther I look into the post-merger periods, the stronger the positive effects for innovation outputs and efficiency. For example, the increase in citation-weighted patents does not show up until the third year after the mergers. This is consistent with the fact that the impact on innovation takes time to realize. This result suggests that ownership by diversified institutions leads to more productive innovation.

To investigate whether the innovation improvement is due to the increase in diversification, I divide the merging institutions into two groups: those with an actual increase in diversification (that is, a decrease in portfolio HHI) after the mergers and those without diversification increases after the mergers. Next, I split the treated firms into two subsamples based on whether or not they are held by a merging institution with an increase in diversification; I then perform two separate difference-in-difference (DID) tests for these two groups. I find that investor diversification improves significantly more for the group of treated firms held by institutions with increased diversification. Similarly, the positive effects on innovation outputs and efficiency are also concentrated in this group of firms. In contrast, the innovation effects are only marginally significant at best for treated firms held by merging institutions that do not increase diversification. These findings support the idea that the positive effect on innovation is driven by an increase in diversification rather than other impacts of institutional mergers.

I also investigate the relation between these effects and the institutional investor types defined by Bushee (1998, 2001). Given that portfolio diversification is one of the factors that Bushee (1998, 2001) uses to define institution types, I was curious to see if the effects that I find go beyond merely the effect of different institutional types. To explore this further,

I focus on the merging institutions that do not change types after the merger and investigate the effects on the treated firms that they hold. In particular, I perform three different DID tests for treated firms held by a merging institution that is a) quasi-indexer before and after the merger; (b) transient before and after the merger; and (c) dedicated before and after the merger. As mentioned above, the purpose of this analysis is to see whether the effect I find still exists even when the institution type is unchanged. I find that the positive effects on innovation still exist for institutions that didn't change types after the mergers. Additionally, the effect persists when I exclude merging events involving the institutions with certain type-changes that are more likely to drive the changes in innovation. Overall, these results suggest that the effect I find cannot simply be captured by changes in Bushee's institution types.

To see if the information complementarity story can explain the effect I find, I explore the cross-sectional difference of the firms' relations with other industries. The information complementary hypothesis suggests that diversified institutional ownership improves innovation because it offers investors access to more varied information. Consider a treated firm held by institution A that merges with institution B. If this treated firm shares a closer relation with the firms in institution B's portfolio, then the information from institution B will be more valuable and have stronger synergy. We should therefore observe a stronger effect under this scenario. To investigate this possibility, I use the TNIC industry data provided by Hoberg and Phillips (2010, 2016), who define a firm's industry peers based on their product similarity as indicated by their 10-K filings. This data allows me to measure how closely a treated firm that is held by one merging institution is related to industries invested in by the other merging institution. I find that the positive effect on innovation is concentrated in treated firms that have closer relations with firms in the other merging institution's portfolio. This finding is consistent with the information complementarity hypothesis. Meanwhile, for firms without TNIC industry peers in the other merging institution's portfolio, the innovation effects are negative for the outputs and insignificant for efficiency. The negative effects are consistent with the negative impact of distraction. That is, if distraction has a negative impact on governance because institutional investors are shifting their attention to other companies, the negative effects should be strongest when these other companies have no similarities with the target firm.

Overall, the empirical results are more supportive of the hypothesis that, in general, improved information complementarity for diversified institutions helps improve firm innovation productiveness, while there is also evidence consistent with a negative impact occurring due to distraction.

This paper contributes to several lines of literatures. First, it contributes to the literature that relates institutional investors with firm values by showing that diversified institutions may be more effective in creating firm values through better innovation productivity. The HHI trend in Figure 1 suggests a tendency for institutional investors to hold more concentrated portfolios in recent years. In 2019, the HHI level was almost double that of the 1980s. This raises a question: Does portfolio diversification have significant implications for firm values and managerial decisions? This paper takes the first step in answering this by analyzing the impact of investor portfolio diversification on firm innovation.

To my knowledge, this paper is the first to explore the effect of institutional investor portfolio diversification on firm values created by innovation. In the context of a broader literature, there is some debate as to whether institutional investors serve as better monitors and thereby increase firm value. Earlier studies on the relation between firm value and institutional investors find mixed results (e.g., Holderness and Sheehan (1988), McConnell and Servaes (1990), Mehran (1995)). Later researchers find that different identities or characteristics of institutional investors have different implications for the value of firms in their portfolios. Bushee (1998, 2001) classified institutional investors by their turnover rates and tendency to hold stocks for longer periods. He finds that institutions with higher turnover frequency (the “transient” investors) are more likely to induce myopic behaviors and a shorter investment horizon for companies in their holdings. Gao, Harford, and Li (2017) document the higher CEO turnover rate in public firms driven by investors’ shorter horizons. Agarwal et al. (2018) find that more transparent portfolio disclosure creates greater career concern for mutual fund managers and induces short-term-focused incentives, which leads to myopic behaviors by the firms they hold. Regarding the effect of institutional investors’ portfolio composition on firm values, a recent line of literature studies the effect of institutional investors when they hold multiple firms; the focus, however, is on how common ownership in the same industry affects competition incentives

and thus governance effectiveness.

This paper also contributes to the corporate governance literature and its connection to innovation. Earlier studies find positive effects of institutional ownership on R&D investments. Francis and Smith (1995) find that concentrated ownership, which is usually associated with institutional block holders, increases R&D investments. Eng and Shackell (2001) also find positive correlation between institutional investor holdings and R&D spending. Aghion et al. (2013) find that institutional ownership improves innovation inputs and productivity. They argue that innovation investment is risky and results in higher uncertainty about the manager's reputation and career concerns; they further argue that monitoring by institutional shareholders can prevent good managers from being fired simply for bad luck, thus increasing the incentives for innovation. More recently, Edmans, Levit, and Reilly (2019) analyze the effect on governance when large institutional investors hold multiple firms in their portfolios. Their theory suggests that a portfolio with more firms and higher diversity can improve governance through both voice and exit. My findings suggest that the composition of institutional investors' portfolio may have implications on governance quality or on the advisory role the investors provide for the company.

The remainder of this paper is structured as follows. Section 2 develops my main hypotheses. Section 3 describes the data and the variables. Section 4 shows empirical analyses. Section 5 presents cross-sectional differences of the effects. Finally, Section 6 concludes the paper.

## **2. Hypotheses Development**

Based on existing literature and theories, I postulate three hypotheses of how investor diversification can impact firm innovation. The literature has documented two potential roles for an institutional investor: a monitor and an advisor. As a monitor, an institutional investor directly or indirectly affect the managers' decisions and make sure their action align with the interests of shareholders; As an advisor, an investor provides the information it gathers and allow the managers to incorporate the information into making better decisions. My first two hypotheses are more related to the investors' monitoring role, while the third hypothesis has more to do with the advisory role.

## 2.1 Limited attention and the ability to monitor

My first two hypotheses are about limited attention on the part of institutional investors. When it comes to innovation, this limited attention can have either a beneficial or a negative impact.

To exert good governance on a firm, institutions need to spend time and effort to do their research and improve the manager's decisions. For example, institutions must pay attention to the firm's performance and participate in shareholder meetings to express their prospect of the company. Institutions must also have a good understanding of the firm's industry. If institutions want to change a firm's investment or financing policies, they will need to develop their own plan and put forth a shareholder proposal. However, institutions have only limited time and resources. The more diversified an institution's portfolio, the less likely it is to put similar effort into all the firms it contains.

Asset pricing literature has long studied the limited attention of institutional investors. For example, Peng and Xiong (2006) study asset prices and find that including investors with limited attention in the model helps explain return co-movements that are otherwise difficult to understand. Hendershott et al. (2021) simulate a model with randomly arriving inattentive investors and find the results consistent with the observed return data. On the other hand, recent studies in corporate finance literature by Kempf et al. (2017) and Liu et al. (2020) also analyze the impact of investor inattention on corporate governance; these studies find that the effectiveness of an institution's governance is significantly lowered when investors are distracted by exogenous events that require attention.

Here, I first conjecture that the effect found by Kempf et al. (2017) and Liu et al. (2020) can be stronger for diversified institutions for two reasons. First, a diversified investor's portfolio contains more industries, which increases the likelihood that it will experience attention-requiring shocks in one of those industries. Second, the limited resource constraints are more likely to be binding for diversified institutions. An institution that invests in 10 different industries is likely to have more constrained resource allocation than one focused on only one or two industries. Therefore, given a distracting event, it is more likely that a diversified institution would have to adjust its attention allocation due to binding constraints.

Although distraction reduces the effectiveness of institution monitoring, this reduction

might be good or bad for firm innovation. If one believes institutional monitoring can help reduce the career concerns of the managers and encourage long-term investment, as Aghion et al. (2013) argue, then institutional inattention may hurt innovation. However, one can argue that institutional investors themselves can have a suboptimal incentive horizon. Bushee (1998, 2001) finds that not all investors have a long-term focus. If institutional investors value short-term profitability and penalize short-term under performance, this can hinder the manager's incentive and ability to invest in innovation (Manso (2011)). In such a scenario, institutional investor inattention can actually encourage managers to focus on long-term investments, including innovation. Note that these two hypotheses do not have to be mutually exclusive and can co-exist empirically.

## **2.2 Diversified institutions may improve innovation due to information complementarity**

Knowledge from other industries may help facilitate more productive innovation. Technology used in one industry may find new applications in another and stimulate innovation ideas. A notable example is the recent surge in Fintech. By exploiting the more advanced technology in the computer science area, the financial services industry has changed significantly over the past decade. Diversified institutional investors are exposed to more diversified information due to their holdings in different industries. If there are complementarities between these varied types of information, diversified investors can generate higher value in innovation than more concentrated institutions. Consistent with the idea that information from different industries has complementarity, Kini et al. (2009) find that international analysts with more diverse portfolios have access to more varied information and can improve their forecast through information complementarities.

Given these different arguments, empirically investigating the effect of diversified institutions is therefore an interesting proposition.

## **3. Data and Variables**

### **3.1 Main Sample and Main Diversification Measure**

The sample for my main analysis is a combination of multiple sources. First, I use the Refinitive 13F institutional holdings database (formerly Thomson-Reuters) to acquire quarterly institutional ownership data and calculate common ownership from 1980 to 2019.

To acquire stock price and industry information, I use the data from the CRSP database. To measure innovation quality, I use the measure constructed and shared by Kogan et al. (2017). I also use the Compustat database for any required balance sheet data. The final sample consists of 168,019 firm-quarter observations and 17,125 distinct firms from 1980 to 2019.

I construct my diversification measure as follows. First, I calculate the portfolio HHI based on the Fama-French 48 (FF48) industry definition for each 13F institution in each quarter.<sup>2</sup> Next, for each quarter in my sample, I sort the 13F institutions by HHI. If an institution has an HHI below the quarter median, I define the institution as *highly diversified*; otherwise, I consider it *less diversified*. Next, at the firm level, I aggregate the percentage ownership from the highly diversified institutions. More specifically, for each firm  $f$  and quarter  $q$ , I calculate the diversified ownership as follows:

$$DivIO_{f,q} = \sum_i \frac{SharesHeld_{i,f,q}}{SharesOutstanding_{f,q}} * HighDiv_{i,q},$$

where  $SharesHeld_{i,f,q}$  is the number of shares institution  $i$  held in firm  $f$  in quarter  $q$ ,  $SharesOutstanding_{f,q}$  is the number of shares outstanding for firm  $f$  at quarter  $q$ , and  $HighDiv_{i,q}$  is an institution-level dummy variable that equals 1 if an institution is classified as highly diversified, and 0 otherwise. Finally, I take the average of the quarterly measures each year as the annual  $DivIO$  measure.

There are two ways to understand the measure. First, it is the portion of outstanding stock of the firm that is owned by the more diversified institutions. Comparing the effect of this measure and the overall institutional ownership can shed light on whether ownership by institutions with greater diversification has stronger or weaker effects. Second, the  $HighDiv_{i,q}$  dummy can be considered a binary diversification measure at the institution level. Viewed in this way, the  $DivIO$  measure is also a weighted measure of how diversified the institutions holding the firm are, with the weight equal to the shares held by an institution. An alternative way to construct the weight is to scale  $SharesHeld_{i,f,q}$  by overall institutional ownership instead of all shares outstanding. If constructed in this way,

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<sup>2</sup> The results in this paper do not depend on the industry definition I choose. I conduct the tests with the Fama-French 30-industry definition, and all the results are qualitatively similar.

the weight would capture the relative importance of diversified institutional investors to the firm comparing with all institutional investors. However, this measure would fail to capture the absolute impact of diversified institutional investors to the firm. Consider a firm with 30% shares held by diversified institutional investors and 20% shares held by other institutional investors, the diversification measure would be the same as another firm with 3% shares held by diversified institutional investors and 2% shares held by other institutional investors, but clearly, the former firm should be affected more by the diversified institutional investors. I therefore choose to scale  $SharesHeld_{i,f,q}$  by all shares outstanding.

One of the concerns of using a binary diversification measure like this is that if the HHI of the median institution has a certain secular trend, the definition of a “diversified” institution may vary across time. As Figure 1 shows, portfolio diversification of the median institution was relatively stable from 1980 to 1998 and from 2000 to 2015. After 2015, there is an increasing trend in median HHI, indicating a decrease in portfolio diversification. Although the change in trend after 2015 may indicate concerns for my panel regressions, this is not a severe concern for my DID tests, which are the main tests driving the conclusion of a causal relation in this paper. The latest merger event in my sample is around 2010, which is outside of the periods in which a clear trend was happening. I also did an alternative test that exclude the mergers around year 2000 when there is a jump in HHI of the median institution. The finding that investor diversification increases after the mergers remains true.

Panel B of Table 1 also shows various characteristics of the highly diversified and less diversified institutions. Diversified institutions are larger institutions and are more likely to be classified as a “quasi-indexer,” which Bushee (2000, 2001) defines as an institution with higher diversification and lower portfolio turnover rate.

### **3.2 Other Variables and Data Sources**

My dependent variables include the number of patents, patent value based on stock market reaction, and the number of citations received. To calculate the dollar value of the patents, I use the same measure as Kogan et al. (2017). I sum up the real patent value ( $xi\_real$ ) of all patents for each firm-quarter. This measure captures the inflation-adjusted market reaction to the patent publication. For the citation-weighted patent, I adjust the



potential truncation problem embedded with the citation data by dividing the raw citation count by the average number of citations for all patents issued in the same quarter. More specifically,

$$Citation_{f,q} = \sum_{k \in P_{f,q}} (1 + \frac{C_k}{\bar{C}_q}),$$

where  $C_k$  is the citation received by patent  $k$ , and  $\bar{C}_q$  is the average number of citations received by all patents issued in quarter  $q$ . When merging different databases, if an observation from CRSP/Compustat does not have a match in the patent database, I replace all innovation measures with zero. Finally, I aggregate all innovation measures at the annual level.

To measure the R&D efficiency, I divide the innovation output measures by the R&D capital (RDC), where R&D capital in year  $t$  is defined as follows:

$$R\&D(Expense)_t + 0.8R\&D_{t-1} + 0.6R\&D_{t-2} + 0.4R\&D_{t-3} + 0.2R\&D_{t-4}.$$

The definition follows Chan, Lakonishock, and Sougiannis (2001) and accounts for the fact that R&D investment has long-lasting effects, and that the R&D output in a given year is a result of investment in the previous years.

For my identification strategy, I use the merger list provided by Lewellen and Lowry (2021) and merge the institutions with 13F holding database.

Panel A of Table 1 provides the summary statistics for the main variables and the control variables. Consistent with the notion that innovation is a relatively rare investment, the innovation measures are highly skewed. The median firm in my sample is not involved in innovation activities; on average, firms produce 8.147 patents per year that are worth \$261 million and receive 17.23 citations.

The average level of institutional ownership (IO) for my sample is lower than that reported in some of the papers in the literature. This is because I apply only minimal sample selection criteria and retain many firms with very low institutional ownership in my sample. For example, comparing with the analysis by Cheng, Wang, and Wang (2022), whose sample consists of 34,500 firm-year observations for the period 1991-2015, my sample contains 116,126 firm-year observations for the same period. This may happen because Cheng, Wang, and Wang (2022) require that the firms in their sample to be included in the MSCI ESG Stats database. Many of the firms in my sample have very low IO. As shown

in Panel A of Table 1, 25% of the firms in my sample has an IO lower than 10%. This result in lower average IO and higher standard deviation for my sample. To make sure that the lower IO level in my sample is indeed driven by different filtering criteria, I investigate the IO level in subsamples of my data when stricter criteria are applied. Specifically, using a list of Russell Indices components from 2006 to 2019, I find that the average IO is 62.24% for firms in the Russell 2000 Index and 77.05% for firms in the Russell 1000 Index.<sup>3</sup>

## 4. Innovation and Institutional Investor Diversification

### 4.1 The Baseline Analysis

If ownership by diversified institutional investors has an impact on governance, it should reflect on some of the firm's decisions. Innovation is an important investment decision that requires a focus on long-term values rather than short-term profits. It is therefore interesting to investigate whether investor diversification has an impact on a firm's innovative activities.

I first attempt to confirm the past findings in the literature that institutional investors positively affect innovation by regressing the innovation measures on institutional ownership:

$$Innovation_{f,t+2} = \alpha + \beta IO_{f,t} + \gamma X_{f,t} + \theta_f + \lambda_{j,t} + \varepsilon_{f,t},$$

where  $IO_{f,t}$  is the fraction of outstanding market cap for firm  $f$  that is owned by the institutional investors at time  $t$ , and  $X_{f,t}$  is a vector of the control variables that includes return on assets (ROA), leverage, cash, Tobin's Q, KZ-index, log of total sales, tangibility, industrial HHI, and a measure for common ownership (C-index, as proposed by Lewellen and Lowry (2021)).  $\theta_f$  and  $\lambda_{j,t}$  are Firm FE and Industry-Time FE, respectively. I impose a two-year lag between the dependent variable and the independent variables because innovation takes time to develop; so, while the current ownership structure is unlikely to affect the simultaneous innovation outputs, it will affect outputs in the future. Most of the control variables are consistent with previous literature. ROA is included as a control in most innovation studies, but the signs are not always consistent. For example,

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<sup>3</sup> For comparison, Crane, Michenaud, and Weston (2016) find that, from 1990 to 2006, the average IO is 52% for firms in the Russell 2000 Index and 65% for firms in the Russell 1000 Index.

ROA coefficients are positive and significant as reported by He and Tian (2013) but are negative in the findings of Agarwal et al. (2018). Most innovation studies find the effects of cash, Tobin's Q, and tangibility to be positive and significant. The common ownership measure, C-Index, does not have a consistent sign across different innovation measures. As Anton et al. (2021) argue, the effect of common ownership on innovation is complex and depends on the interaction of the competing forces of technology spillover and product market spillover. It is somewhat confusing to see that KZ-Index has a positive effect on innovation as the measure captures the extent to which the firm is under financial constraints, which should be negatively correlated with investments—including innovation. This might happen because the components of KZ-Index include variables like Tobin's Q, Cashflow, and Leverage, which I also control for in the regression. It is possible that part of the effects for KZ-Index is absorbed by these other variables and the remainder of the effect shows a positive sign. If I remove the variables included in the calculation of KZ-index from the regressions, the coefficients for KZ-index flip to negative for all specifications but are statistically insignificant for number of patents and R&D expenses.

To calculate measures for innovation output quality, I use the dollar value of patents following Kogan et al. (2017). This measure uses the stock price movements after a patent is issued to proxy for its economic value for the firm. For a firm  $f$  in quarter  $q$ , the total innovation value in that quarter is as follows:

$$Ptvalue_{f,q} = \sum_{k \in P_{f,q}} \xi_k ,$$

where  $P_{f,q}$  is the set of patent applications filed at quarter  $q$ , and  $\xi_k$  is the filtered stock price reaction following patent issuance.<sup>4</sup> I then sum up the patent value in all quarters within a year to get the annual measure. I also include the number of patents (*NumPatent*) and the citation-weighted patent (*Citation*) in my main analysis. For all innovation variables, I use  $\ln(1+innovation)$  as the dependent variable. As Table 2 shows, the coefficients for *IO* are all positive and significant. A one standard deviation increase in institutional ownership leads to 1.78% ( $0.308 \times 0.0577$ ) more successful patent

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<sup>4</sup> Kogan et al. (2017) use the stock price reaction in the two-day window following the publication of patent grants to evaluate the patent's economic value for the firm. Their approach filters out the potential impact of other news within that window and addresses the market's pre-grant assessment of the likelihood that the application would be successful.

applications and 2.94% ( $0.308 \times 0.0955$ ) higher monetary patent value. The number of citations received also increases by 2.54% ( $0.308 \times 0.825$ ). The positive coefficients are consistent with the findings by Aghion et al. (2013), who find in their OLS regression that a 10% increase in *IO* results in about 6% increase in number of citations, but the economic significance is much smaller. Two reasons drive this difference. First, I control for firm and industry-time fixed effects, while Aghion et al. (2013) does not account for the fixed effects in their baseline OLS regressions. Second, my sample spans 1980–2019, which differs from the sample period in the Aghion et al. (2013) analysis. When I do not control for the fixed effects and use the same period (1990–1999) as the analysis by Aghion et al. (2013), I find that a 10% increase in *IO* is associated with 6.86% increase in citation. This is similar to the level found by Aghion et al. (2013).

To investigate whether diversified institutional investors affect the innovation decision, I calculate *DivIO*—that is, the institutional ownership of highly diversified institutions—to examine if this type of institutional ownership has a different impact than the overall ownership. As explained above, *DivIO* can also be considered a weighted diversification measure of the institutions that hold shares of the firm.

It would be interesting to see whether different *DivIO* has an incremental effect on innovation given the level of overall institutional ownership. However, *DivIO* and *IO* are highly correlated. In my sample, the correlation coefficient of these two variables is approximately 0.95. Therefore, it is problematic to simply include *DivIO* in the panel regression as there will be a collinearity issue. To work around this issue, I perform two different tests.

First, to examine the marginal effect of *DivIO* given a similar level of overall *IO*, I perform a dependent sort on the two variables and see whether the innovation levels are different for different portfolios. More specifically, for each year, I first sort all the firms on *IO* and divide the sample into quintiles. Then, for each *IO* quintile, I further sort the firms on *DivIO* and form *DivIO* quintiles within the *IO* portfolio. This gives me 25 portfolios for each year from 1980 to 2019. Next, as Table 3 shows, I calculate and summarize the time-series average of different variables. Panels C–E in Table 3 show the average innovation for each portfolio. Except for the bottom *IO* quintile (*IO\_Q1*), which does not have much overall ownership to begin with, *DivIO* is positively associated with

all innovation measures for all other *IO* quintiles. The top *DivIO* quintiles always have significantly higher innovation than the bottom *DivIO* quintiles.

One caveat of interpreting the Table 3 numbers is that due to the high correlation between *IO* and *DivIO*, the quintile sort does not fully eliminate *IO* variation for different *DivIO* portfolios in the same *IO* quintile. As an example, take Panel A's third column in Table 3. It shows that, within the *IO\_Q3* quintile, the top *DivIO* portfolio has an average *IO* level of 40.8%, which is about 8.8% higher than the bottom *DivIO* quintile. This difference in *IO* can also partly contribute to the top *DivIO* portfolio's higher innovation. However, if we compare, for example, the top *DivIO* portfolio in *IO\_Q2* and the bottom *DivIO* portfolio in *IO\_Q3*, the former has a higher ownership from diversified institutions (20.0%) than the latter (13.5%) but has a lower overall ownership (22.1% vs. 32.0%, respectively). But all innovation variables are higher for the top *DivIO* portfolio. In other words, the top *DivIO* portfolio in *IO\_Q2* has higher innovation outputs than the bottom *DivIO* portfolio in *IO\_Q3*, despite having lower overall institutional ownership; this is likely due to the higher ownership by the diversified institutions. Similar comparison results are true for all columns in the table, thus suggesting *DivIO* may have some effects independent of the overall *IO*. I also run regressions that use *DivIO* quintiles as independent variables. The results are reported in Appendix 2 and confirm that *DivIO* is positively correlated with innovation, controlling for the levels of overall *IO*.

My second test aims to confirm the effect of *DivIO* on innovation in a panel regression setting. To avoid the collinearity issue mentioned above, I perform an orthogonalization on *DivIO* to filter out the part that is correlated with the overall *IO*. Specifically, the “orthogonalized *DivIO*” is equal to the error term of the following regression:

$$DivIO_{f,t} = \alpha + \beta IO_{f,t} + \varepsilon_{f,t}.$$

This orthogonalized variable measures how diversified a firm's investors are given the level of overall institutional ownership. Intuitively, the above regression tells us the average level of diversified ownership given the level of overall *IO*. So, a positive error term would indicate that the firm's diversified ownership is higher than expected given its overall *IO* level. Similarly, if the error term is negative, it means the firm's institutional investors are less diversified than expected. I then estimate the following regression:

$$Innovation_{f,t+2} = \alpha + \omega Orth\_DivIO_{f,t} + \mu IO_{f,t} + \gamma X_{f,t} + \theta_f + \lambda_{j,t} + \varepsilon_{f,t},$$

where *Orth\_DivIO* is the orthogonalized *DivIO* measure, and *IO* is the overall institutional ownership. Table 4 shows the results. The coefficients of *Orth\_Div\_IO* indicate that ownership by institutions with different diversification levels has a significantly different impact on innovation. The coefficient  $\omega$  is positive and significant after controlling *IO* in all specifications, indicating that if a firm's institutional investors are more diversified than suggested by the overall *IO*, it is likely to have better innovation outputs. The coefficient  $\mu$  for *IO* is positive for *PtValue* and *Citation*, suggesting that general *IO* is still helpful for the innovation, and not all the effect is from the more diversified investors. According to the results, a one standard deviation increase in *Orth\_DivIO* is associated with 0.8% higher R&D expenditures. In terms of innovation outputs, a one standard deviation increase in diversification is associated with approximately 1.56% more patents that have 3.02% higher monetary value and receive 1.56% more citations. The economic magnitude of the effect is comparable to that of *IO* in the same regression.

To see if the correlation between *Orth\_DivIO* and innovation depends on the level of overall institutional ownership, I run another panel regression. It is an interesting test because the portfolio analysis in Table 3 shows that the relation between *Div\_IO* and innovation may differ for different *IO* levels. Table 5 reports the regression's results:

$$Innovation_{f,t+2} = \alpha + \omega_1 Orth\_DivIO_{f,t} + \omega_2 Orth\_DivIO_{f,t} \times HighIO_{f,t} \\ + \mu IO_{f,t} + \gamma X_{f,t} + \theta_f + \lambda_{j,t} + \varepsilon_{f,t},$$

where *HighIO<sub>f,t</sub>* is a dummy variable that equals 1 if the overall *IO* is greater than the median in year *t*, and zero otherwise. The coefficient  $\omega_2$  is not significant for all specifications, indicating that there is no significantly different relationship between *Div\_IO* and innovation at different *IO* levels.

The results in Table 4 and Table 5 show positive correlation between investor diversification and firm innovation. However, the results are subject to several endogeneity issues and cannot be used to draw a causal conclusion. For example, a potential selection issue is that innovative firms are more likely than less creative firms to attract diversified institutional investors. Boone et al. (2020) find that diversified investors prefer to hold firms with less firm-specific diversification and greater market differentiation. The results are also subject to the fact that diversified investors tend to be larger or have more resources

than other investors. As Table 1 shows, in my sample, the highly diversified institutions are indeed larger investors with stable holdings. It could be that such firms become diversified because they are more resourceful when it comes to governance. Consistent with this notion, Van Nieuwerburgh and Veldkamp (2010) show that an institution's degree of diversification depends on its ability to collect information about future asset values. In the following analyses, I will exploit the merger of financial institutions to identify plausibly exogenous changes in institutional diversification and try to address these potential endogeneity concerns.

#### **4.2 Merger of financial institutions as exogenous variation in diversified institutional ownership**

Financial institution mergers offer an opportunity to identify exogenous changes in diversified institutional ownership, as merged institutions are likely to be more diversified than they were before the merger. Intuitively, if two institutions invest in different industries, their merged portfolio is likely to be more diversified than their individual pre-merger portfolios. However, this may not be true for all portfolios. Mathematically, one can construct extreme examples in which the industry HHI increases for the merged portfolio (thus resulting in lower diversification). Given this—and to ensure that it is reasonable ex-ante to expect mergers to increase portfolio HHI for realistic portfolio holdings of actual institutions—I perform a simulation for hypothetical mergers using actual portfolio holdings of 13F institutions. For each quarter, I randomly select 50 institutions from the 13F institutional holding database and do the pair-wise hypothetical mergers across all possible pairs among the 50 institutions. (The draws for different quarters are independent). I then calculate the portion of institutions with a drop in HHI after the mergers.

Figure 2 shows the results: not all possible mergers will increase portfolio diversification for the newly merged institution. However, for all quarters, 70–80% of the hypothetical mergers did increase portfolio diversification for the involved institutions. Panels A–C in Table 6 provide a summary of additional stats for the hypothetical mergers. Panel B shows that, on average, the institutions used in the simulation have a similar level of diversification to my test sample, while Panel C shows that for the simulated mergers, the diversification increase is statistically significant. As these results show, it is reasonable to say that mergers are likely to increase portfolio diversification in most cases.

Probably more importantly, as He and Huang (2017) and Lewellen and Lowry (2021) argue, mergers are unlikely to be driven by the characteristics of individual portfolio firms. Therefore, from the firm's perspective, the increase in diversified institutional ownership can be considered exogenous.

I use the merger list provided by Lewellen and Lowry (2021) to identify the actual mergers during my sample period. To be included in the list, the merger must satisfy three criteria: (1) The merger occurred between 1980 and 2015. (2) The target institution was incorporated in the United States. (3) Both the acquirer and target had an SIC code between 6000 and 6999. The list includes 64 merger events.

To ensure that the mergers increase portfolio diversification in my sample institutions, I examine their portfolios in the time period around the merger dates. For this analysis, I include all merging events in which the acquirer institution (*mgrno*) continues to exist immediately after the merger completion date. This leaves 61 of the 64 mergers in my sample. I then investigate these mergers to examine how different the acquirer and target portfolios are before the merger. As Panel D in Table 6 shows, approximately 65% of the merging institutions increase their level of diversification after the mergers, and the increase is statistically significant.

For a firm held by one of the merging institutions, the degree of portfolio diversification of their institutional investors would increase after the merger. Because the mergers are unlikely to be driven by individual firms in the portfolio, this change is considered exogenous. Next, I design a DID test as follows: I define the *treated firms* as firms held by one of the merging institutions before the merger, but not by both institutions. I exclude the firms held by both institutions because their ownership will become more concentrated after the merger, which may confound the effect of diversified ownership that I want to identify. I use all firms not held by either merging institution as the control group. For this experiment, I drop the year when the mergers happen and compare the variables of interest before and after the mergers to identify changes that are different between the treated and control groups. I use a seven-year window for my DID test—that is, for each variable of interest, I compare the value three years after the event with the value up to three years before the event.

To discern how diversified ownership changes around merger completion dates at the



firm level, I first perform a DID test on my firm-level diversification measure (*Orth\_DivIO*) and compare the changes in diversified ownership between the treated and control firms. Figure 3 shows the *Orth\_DivIO* trend around the merger completion date for the treated and control groups. As the graph shows, there is no pre-existing trend between the treated and control firms before the merger, although there is a slight difference between the groups in the year before. The diversified ownership measure jumps upward after the mergers only for the treated firms. To view this in a regression setting, I estimate the following regression on *Orth\_DivIO* :

$$\begin{aligned} Orth\_DivIO_{m,f,t} = & \alpha + \beta Treated_{m,f} + \gamma Post_{m,t} + \delta Treated_{m,f} \times Post_{m,t} \\ & + \theta_f + \omega_m + \varepsilon_{m,f,t}, \end{aligned}$$

where  $Treated_{m,f} = 1$  if firm  $f$  is held by either the acquirer or the target merger institution  $m$  prior to the mergers, and it equals 0 otherwise.  $Post_{m,t}$  indicates whether year  $t$  is after the merger completion date.  $\theta_f$  and  $\omega_m$  are firm fixed effects and merger fixed effects, respectively. The coefficient of interest is  $\delta$ , which captures the change in diversified ownership for treated firms relative to control firms around the mergers. In Table 7, column 1 reports the DID results without controls, while column 2 controls for ROA, Tobin's Q, and the log of equity value, which are variables that prior literature (e.g., Chan et al. (2002), Fang, Tian, and Tice (2014)) considered to be correlated with institutional ownership. In both models, coefficient  $\delta$  is positive and significant, which confirms the trend in Figure 2 and indicates that the mergers positively affect the diversified ownership for the treated firms. The orthogonalized diversified ownership increases by about 1.1% after the merger for the treated firms, which is about the same level as that for the median firm in my sample. As discussed earlier, if the median institutional HHI changes around the merger, the definition of "diversified" institution will differ before and after the merger, which makes it harder to interpret the DID results. In column 3, I repeat the test excluding the merger events around year 2000, when there is a jump in median HHI. The result is not affected. Column 4 shows the results of the DID test in a dynamic panel setting; it shows that the biggest jump of *Orth\_DivIO* occurred in the first year after the mergers. The sample sizes of these tests are significantly larger than those of the panel regressions because I construct the treated and control groups for each merger, and the same firm-year can appear in multiple merger events.

### 4.3 Difference-in-Difference test for innovation

Having validated my experiment design, I proceed with the DID tests on innovation. To see if the treated and control groups have different pre-existing trends for my innovation measures, I calculate the average innovation measures for each group and each year around the merger completion dates. Figure 3 shows the results. Although the levels of innovation measures are higher for the treated group before the mergers, statistically, the DID test only requires the focal variables to have a parallel trend before the shock. As Figure 4 shows, there is no obvious trend in innovation measures for either the treated or control firms before the merger events; the innovation measures, however, clearly increase more for the treated firms than the control firms after the merger.

I then perform the DID test on innovation in a regression setting:

$$\begin{aligned} Innovation_{m,f,t} = & \alpha + \beta Treated_{m,f} + \gamma Post_{m,t} + \delta Treated_{m,f} \times Post_{m,t} \\ & + \rho X_{f,t} + \theta_f + \omega_m + \varepsilon_{m,f,t}, \end{aligned}$$

where  $Innovation_{m,f,t}$  is one of the innovation output measures or R&D expenses. Note that the time subscript of the dependent variable is  $t$  instead of  $t + 2$ , which means that I am effectively comparing the quality and quantity of successful innovation applications three years after the mergers with the innovation three years before the mergers. This design is standard in the innovation literature that uses DID to identify causal relationship (e.g., He and Tian (2013) and Fang, Tian, and Tice (2014)), but a potential concern of this test is that innovation is a long-term investment that may take years to produce results. Therefore, it is possible that the innovation output one year after the mergers is affected by factors that existed before the merger completion dates rather than the mergers themselves. To account for this, recent researchers have run an additional test in the dynamic DID setting—that is, they have included separate dummies for each year around the merger (see, e.g., Fu et al. (2020) and Agarwal et al. (2018)). In the dynamic setting, one can identify the trend of innovation measures on an annual basis around the event. If there is no apparent trend for the years before the event, and the difference between the treated and control groups increases after the event, then it is consistent with the hypothesis that the post-event effect on the innovation is driven by the event. In the context of this paper, if I find no different trend before the mergers between the treated and control groups, but the interaction terms between *Treated* and the post-merger year dummies are all significantly positive and

increasing from years +1 to +3, then it is more likely than not that the difference is driven by the merger events. Although it is impossible to entirely rule out any other explanation, any alternative interpretation must satisfy the following: 1) The factor that induces the effect is something that systematically occurs at a time very close to the merger completion dates across different merger events. 2) It affects only the firms held by the merging institutions. 3) If it is something that happens before the mergers, it does not show any effect on innovation until the mergers are completed. Tables 8 and 9 show my standard DID regressions on different innovation measures, and Table 10 shows the dynamic DID tests.

In Table 8, the coefficients show that innovation outputs for the treated group have a larger increase after the mergers compared to the control firms. For the three years after the merger, the number of successful patent applications for the treated group increases by 0.61%, and the patent value increases by 0.94% more than the control group. The DID coefficient for citation is not statistically significant but, as Table 10 shows, this is because the effect on citation shows up only in later years. On the other hand, R&D investments for the treated and control firms do not show different trends after the mergers. While this indicates that diversified institutional ownership does not lead to greater investments in the R&D, it can improve the efficiency of such investments. For example, information from other industries may help the R&D process by increasing the success rate and producing more valuable innovation results.

To see if this is true in my sample, I perform the DID tests on the innovation efficiency measures. For this test, to proxy for the efficiency of innovation investment, I include four different measures: Citation/R&D, Citation/RDC, PatValue/R&D, and PatValue/RDC. R&D is the R&D expenditures, and RDC is the R&D capital measured as  $R\&D_t + 0.8R\&D_{t-1} + 0.6R\&D_{t-2} + 0.4R\&D_{t-3} + 0.2R\&D_{t-4}$  (Chan, Lakonishok, and Sougiannis (2001)). Table 9 summarizes the results. As the table shows, R&D investment efficiency for the treated firms significantly increases after the mergers; following the mergers, each dollar invested in R&D results in 0.04 more citations and \$0.05 higher citation values, which is 40% and 22% of the mean Citation/RDC and PatValue/RDC, respectively. Because all efficiency measures have similar results, for the sake of brevity, I will report only the result for PatValue/RDC in the following analyses.

I next perform the dynamic DID regression in the following setting:

$$\begin{aligned} Innovation = & \alpha + \beta Treated + \delta_1 Treated \times Pre2 + \delta_2 Treated \times Pre1 \\ & + \delta_3 Treated \times Post1 + \delta_4 Treated \times Post2 + \delta_5 Treated \times Post3 \\ & + \gamma_1 Pre2 + \gamma_2 Pre1 + \gamma_3 Post1 + \gamma_4 Post2 + \gamma_5 Post3 + \rho X_{f,t} + \theta_f + \omega_m + \varepsilon_{m,f,t}, \end{aligned}$$

where *Pre2* and *Pre1* are dummy variables for 2 years and 1 year prior to the merger event, and *Post1* – *Post3* are dummy variables for 1, 2, and 3 years after the merger, respectively. Note that because my regression includes the *Treated* dummy and omits the *Pre3* indicator,  $\delta_1$  to  $\delta_5$  are the difference-in-difference coefficients for the respective years relative to year -3. For example, consider year -2. The difference in innovation between the treated and controls in year -2, controlling for  $X_{f,t}$  and the fixed effects, is

$$(\alpha + \beta + \delta_1 + \gamma_1) - (\alpha + \gamma_1) = \beta + \delta_1.$$

Similarly, the difference between the treated and controls in year -3 is

$$(\alpha + \beta) - (\alpha) = \beta.$$

Therefore, the difference-in-difference coefficient for year -2 (relative to year -3) is

$$\beta + \delta_1 - \beta = \delta_1.$$

The interaction terms  $Treated \times Pre2$  and  $Treated \times Pre1$  in Table 10 show no significantly different trends in innovation measures between treated and controls prior to the mergers. Only two out of eight such coefficients are marginally significant. The insignificance of  $\delta_1$  and  $\delta_2$  indicates that the difference in innovation measures between treated and controls are similar across years -3, -2, and -1. On the other hand, coefficients  $\delta_3$  to  $\delta_5$  are monotonically increasing across all innovation measures. For example, for  $\ln(1+NumPat)$ , the difference between treated and controls in the first year after merger shows no significant difference from that in year -3, while the difference is enlarged to 1.51% for year +3 and is significant at 1% ( $\delta_5$ ). Overall, Tables 8–10 show that the mergers have stronger positive effects on innovation for the treated firms.

#### 4.4 Robustness Tests

I also perform several robustness tests to support the main results. The results of these tests are reported in Table 11. First, I repeat the DID test with a matched sample. For this test, I perform a one-on-one match for each treated firm with a non-treated firm based on Mahalanobis distance. The matching metrics include all control variables I use in my main

tests. The match is non-replacing, which means that if a firm is matched with one treated firm, it cannot be matched again with a different treated firm. The comparison of the matching variables in the treated group and the control group are reported in Appendix 3. As shown in Appendix 3, the quality of the match is not perfect. The average levels of the matching variables are significantly different between the treated firms and the matched control firms. Still, although the matched sample does not fully eliminate the potential difference between the treated and control firms, this test should still help reducing those differences as compared with my baseline specification, and it is reassuring to see that all the results remain qualitatively similar.

As mentioned earlier, one of the concerns of defining the “diversified” institutions as those with below-median HHI is that if there is a secular trend for institutional HHI in my sample period, the definition of a diversified institution would not be consistent across time. However, the merger events I used all occurred between 1984 and 2010, during which period there was no particular trend in median HHI except for a jump around 2000. To avoid cases in which the definition of a “diversified” institution is not consistent before and after the mergers, I repeat the DID tests excluding the merger events around year 2000 (from 1997 to 2003). Panel B in Table 11 show the DID coefficients for the tests; the results are qualitatively similar to my baseline specification.

Next, to account for the concern that innovation in the first year after mergers may be affected by factors from before the merger, I induce a different time lag between the post- and pre-merger periods and repeat the DID tests. Panels C–E in Table 11 show the coefficients for the DID interaction terms. For the test in panel C, I drop years -1 and -2 prior to the mergers but extend the pre-merger periods to year -5. Also, the innovation output measures (*NumPat*, *Citation*, *PtValue*) I used in this test are 2 years ahead of the explanatory variables ( $t + 2$ ). Therefore, the test effectively compares the patent outputs from years -3 to -1, with outputs from years +3 to +5. The tests in panels D and E are similar. In both tests, I extend the event period and drop the year immediately before and after the merger year (that is, I drop years -1 and +1). For panel D, on the other hand, I retain the same test window up to year +3 and year -3, while in panel E, I extend the window from -4 to +4 so that I still have 3 years of observations in both the pre-merger and post-merger periods. All coefficients reported from panels C–E are similar to the main

results and support the notion that the mergers increase innovation for the treated firms.

I also do an IV regression based on the merger events. In this test, I perform a 2SLS panel regression using the instrument variable *Event*, where *Event* equals 1 for a firm *f* in year *t* if the firm is the treated firm and is in the post-merger period for at least one of the merger events in my sample; otherwise, it equals 0. The first stage regression regresses diversified ownership measure *Orth\_DivIO* on the instrumental variable *Event* and other control variables, and the second stage regresses the innovation measures on the fitted *Orth\_DivIO* in the first stage. Panel F of Table 11 shows the results. The first stage result is very significant. Being identified as a treated firm in the mergers would increase the orthogonalized diversified ownership by 0.5% and is significant at 1% level. The Cragg-Donald Wald F-statistic of 76.076 indicates a very strong identification of the instrument.<sup>5</sup> As for the second-stage regression, although not statistically significant, all second-stage coefficients are still positive. The IV approach effectively compares the innovation of *Event* firms with that of all other firms at any given time rather than measuring the changes in innovation of a firm before and after the event. It is possible that the effect detected by this approach is not large enough to be statistically significant. However, it is still good to see that the coefficients are at least positive. For a rough idea of the economic scale, if we accept that being an *Event* firm would increase the orthogonalized diversified ownership by 0.5% on average (as indicated by the first-stage regression), this would induce a 0.597% ( $0.5\% \times 1.1942$ ) increase in the number of patents, a 0.650% ( $0.5\% \times 1.2999$ ) increase in patent value, and a 0.813% ( $0.5\% \times 1.6260$ ) increase in citation-weighted patents. For an average firm in my sample, this accounts for 0.05 more patents, 1.70 million higher patent values, and 0.14 more citations. Still, the scales of the effects are too small to be statistically significant.

## 5. Cross-Sectional Differences of the Effects

### 5.1 Merging institutions with actual increase in portfolio diversification

Although the institutional mergers are exogenous to the firm, it is still possible that the positive effect on innovation is driven by other merger-related changes rather than by

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<sup>5</sup> Compared with the Stock-Yogo critical value of 16.38.

increased investor portfolio diversification. To account for this possibility, I divide the treated firms into two groups and perform two different DID tests for each group. The first group is what I call the “increased diversification” sample, which consists of treated firms held by the merging institutions whose portfolio diversification increased after the mergers. The second group consists of treated firms held by the merging institutions whose portfolio diversification did not increase after the mergers. Note that all treated firms in my samples are held by only one of the merging institutions, so every firm can be assigned to one of the two groups. I first examine the changes in firm-level institutional investor diversification for the two groups. The DID tests reported in Table 12 show that the increase in *Orth\_DivIO* is more pronounced in the treated firms held by the institutions with an actual increase in portfolio diversification. For the “non-increase” sample, the increase in *Orth\_DivIO* is only marginally significant and much smaller in scale.

Table 13 shows the DID results on innovation for each group. Columns 1, 3, 5, and 7 tabulate the results for the increased diversification sample, while columns 2, 4, 6, and 8 provide the results for the non-increased group. As the first 6 columns show, the positive effects on innovation outputs are concentrated in treated firms whose investors experience an actual increase in diversification after the mergers. All DID coefficients are positive and significant for the increased diversification group. Note that the increase in citation-weighted patents is not significant in the overall sample test, but it is very significant for this subsample. For the treated firms without an actual increase in diversified ownership, the DID coefficients are either insignificant or weakly negative with marginal significance. In contrast, columns 7 and 8 show that the increase in R&D investment efficiency is also higher and more significant in the increased diversification group than the non-increased group, suggesting that the improvement in R&D efficiency is also mainly due to the increase in portfolio diversification. Overall, Table 13 indicates that innovation improves only for the firms with increased diversified ownership.

## 5.2 Interaction with institutional investor types

The second cross-sectional difference I explore is the difference in institutional investor types. Bushee (1998, 2001) categorizes institutional investors into different types based on their portfolio diversification and turnover rates. Specifically, he defines institutional investors as *dedicated (DED)* if they have lower portfolio diversification and

a low portfolio turnover rate; as *transient* (*TRA*) if they have high portfolio turnover rate and are highly diversified; and as *quasi-indexer* (*QIX*) if they are highly diversified but have a low turnover rate. Because portfolio diversification is one of the metrics that Bushee uses to define the investor types, it is important to understand whether the effect I find can be simply captured by the changes in these investor types. For this test, I use the time-varying institution type definition provided by Bushee.

Table 14 summarizes the changes in investor types for the merging institutions. This summary includes 64 acquirers and 64 target institutions. After the merger, an institution's investor type may change or remain the same. Many institutions in my sample are QIX both before and after the mergers (49%), and no institution changes from TRA to DED after the mergers.

If a merging institution changes its type after the merger, interpreting the DID result is difficult as one cannot distinguish whether the effect is due to the change in institutional types or the increase in diversified ownership. Moreover, a change from QIX to TRA may have totally different implications than a change from QIX to DED. So, simply controlling for the post-merger institutional type does not solve the issue. Therefore, to understand the different impacts of diversified ownership on different institution types—and to achieve a more interpretable result—I focus only on cases in which the institutional types do not change after the mergers. More specifically, I divide the treated firms into three groups: those held by a merging institution that is transient both before and after the mergers (the *Transient group*); those held by a merging institution that is a quasi-indexer both before and after the mergers (the *QIX group*); and those held by a merging institution that is dedicated before and after the mergers (the *DED group*). I then perform separate DID tests for each of the three groups. Table 15 reports the results. Panel A shows results for the DED group, panel B for the QIX group, and panel C for the TRA group.

If the effect I find is not fully explained by the investor types, I should find significant results for at least some of these groups where the institutional type does not change. Note that I am constructing the subsamples based only on the merging institutions' types rather than on the average types of all the firm's institutional owners because the merging institution is the only investor whose portfolio diversification is affected by the merger. As a result, if I want to see if the investor types have a confounding effect with diversification,



it is the merging institution's type that matters.

As Table 15 shows, the DID coefficients for the innovation measures are positive and significant for both the DED group and the TRA group, but they are not statistically significant for the QIX group—except for *Citation*, which shows a negative sign and is significant at a 1% level. One of the reasons that innovation for the QIX group does not show significant improvement is that this group sees the least increase in the diversified ownership measure after the merger among the three. In an unreported test, I find that, compared with the control group, *Orth\_DivIO* increases only 0.4% for the treated firms in the QIX group, while the same number is 1.7% for the DED group and 2.5% for the TRA group. The important fact here is that the positive effect remains significant for some merging institutions that do not change type. This suggests that my results cannot be fully explained by changes in Bushee's institutional types.

In addition to focusing on the firms whose institutional investor type remains the same before and after the mergers, an alternative approach to make sure my results are not fully driven by the change of institutional types is to take out certain type changes that are inherently associated with an increase in diversification and see if my results still hold after excluding these firms. Since QIX and TRA are both defined as institutions with higher diversification, a change from DED to either QIX or TRA would imply an increase in diversification. If one wants to argue that my findings can simply be explained by the change of Bushee's institutional types, these kinds of changes are most likely to be the ones that drive my results. Panel D in Table 15 reports the results after excluding the merging institutions that change from DED before the mergers to QIX or TRA after the mergers. As it shows, the results continue to hold when I exclude these institutions, with the exception of citation count that shows an insignificant coefficient.

Looking closer at the results in Table 15, although the DID coefficients are positive and significant for both the DED and the TRA group, the coefficients for innovation outputs are larger for the TRA group. This difference is statistically significant at a 5% level. This observation can be consistent with the distraction story because transient investors tend to have shorter horizons and to not focus on long-term investments such as innovation. The distraction story suggests that when such investors shift their focus elsewhere and involve less in the firm manager's decision, it can be beneficial to the firm's innovation productivity.

However, it would be perhaps incorrect to conclude that the distraction hypothesis is driving my results with this observation alone. Especially when the hypothesis cannot explain the positive effect of diversification in the DED group and the similar innovation efficiency coefficients in the DED and the TRA groups.

Overall, I would argue that Table 15 shows that my effect is not merely driven by Bushee's investor types, but it requires further investigation to learn more about the channel. I will do this in my next test.

### **5.3 Firm relationship with other industries**

To understand whether the information complementarity channel is in play, I next explore whether a closer relation with firms in other industries would strengthen the positive effect on information. To test this conjecture, I utilize the TNIC data shared by Hoberg and Phillips (2010), who define the industry peers for each firm based on the product similarity described in the firms' 10-K filings. A firm-pair is more likely to be defined as *industry peers* if their 10-K filings show higher similarity in their product description. Using this newly defined industry network, I design the following test based on the assumption that if two firms are in the same TNIC industry, they are more closely related, and shared information is more likely to have a complementary effect. To differentiate the TNIC industry from the traditional industry definition, I will use the term "in the same TNIC network" to indicate when two firms are peers as defined by the TNIC industry.

I design my test as follows. For each treated firm in my sample that is held by an institution, say, institution A, that merges with institution B, I examine all firms in B's portfolio. If at least one firm in B's portfolio is from a different FF48 industry but is in the same TNIC network as the focal treated firm, then I assign the treated firm to the *Related* group; otherwise, I assign it to the *Non-Related* group. The idea is that the firms in the *Related* group are more closely related to firms held by the other institution from a different industry. Therefore, there should be more significant benefit of information complementarity after the merger for these firms. On the other hand, the firms in the *Non-Related* group have less connection with firms outside their industry. As a result, even though the portfolio diversification increases for the merged institution after the merger, the benefit from information complementarity should be limited for *Non-Related* group.

firms. I then compare the DID results between the two groups; Table 16 summarizes the results.

As Table 16 shows, the positive effect on innovation is concentrated in the *Related* group. Again, recall that the coefficient for a citation-weighted patent is not significant in the overall DID sample, but it is positive and significant for the *Related* subsample. On the other hand, the DID coefficients are mostly negative and significant for the *Non-Related* group. The negative signs for this group are consistent with the investor distraction hypothesis. Intuitively, if an institutional investor's portfolio diversification reduces its attention on a focal firm and has a negative impact on governance, that negative impact would be most prominent when the focal firm has little to no relation with firms in other industries. For a treated firm in the *Non-Related* group, investor diversification increases after the mergers when firms in different industries are included in its portfolio; however, in such cases, the treated firm has little in common with these other firms. The diluted attention's negative effect is therefore heightened in this situation.

Overall, results in Table 16 support the information complementarity story and the existence of potential negative effects from the distraction story.

## 6. Conclusion

The purpose of this paper is to explore the relation between institutional investor portfolio diversification and the impact on its portfolio firms. In particular, I investigate how investor portfolio diversification can affect a firm's innovation productivity and efficiency.

Using an exogenous shock on diversified ownership driven by institutional mergers, I find a positive causal relation between institutional investor portfolio diversification and the firm's innovation output and R&D investment efficiency. For firms held by the merging institutions, the R&D measures have significantly larger increases than the control firms after the mergers, and this effect is stronger later in the post-merger periods. The cross-sectional tests support that the effect is driven by information complementarity across different industries. In other words, a diversified investor has access to more information from different industries, and it can help to provide better advice or to urge the managers to make better decisions for the firms when it comes to innovation. Although the overall

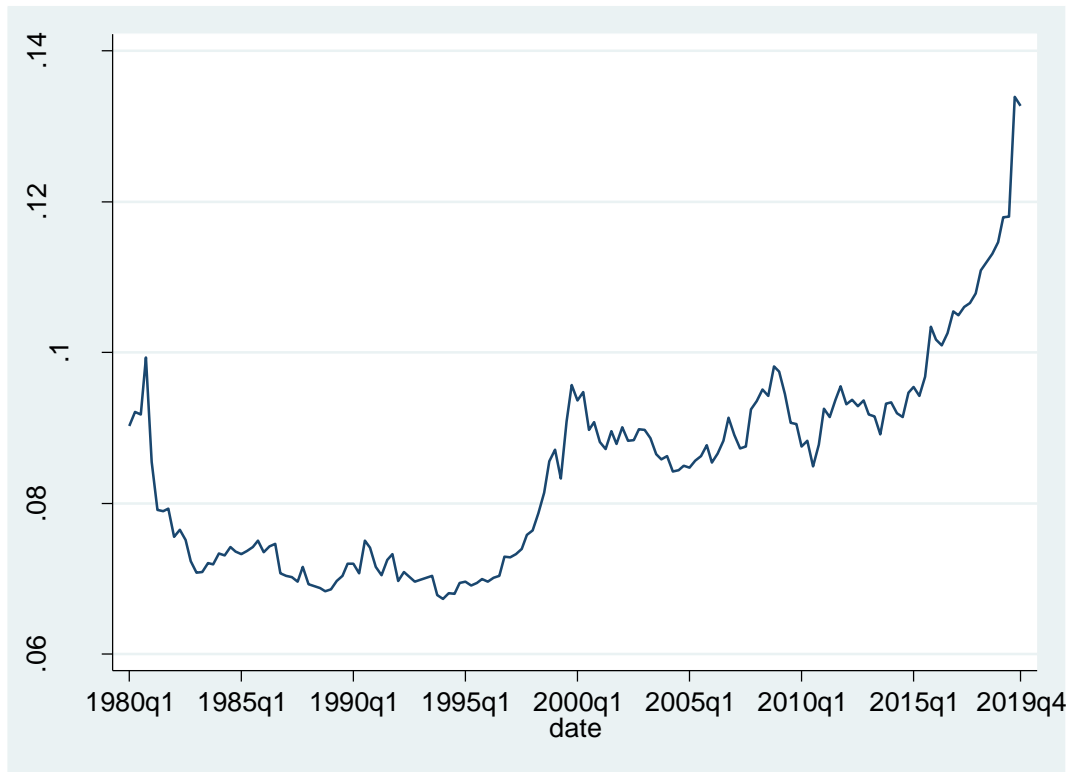
effect of investor diversification is positive on innovation, the empirical evidence also indicates potential impacts from the distraction effect as portfolio diversity increases. However, these effects are subject to specific situations (i.e., when the firm is held by transient institutions or when the firm has low connections with other firms) and are dominated by the information complementarity effects in general.

Overall, the findings in this paper suggest that the degree of diversification of an institutional investor's portfolio can have real impacts on the values and decisions of the firms in its portfolios. Potential future research can investigate its impact on other dimensions aside from innovation.

**Figure 1**

**Trend with median HHI of the institutions**

Figure 1 shows the progression of the median HHI for all 13F institutions throughout my sample period. Except for a jump around 2000, portfolio diversification of the median institution was relatively stable from 1980 to 1998 and from 2000 to 2015. After 2015, there is an increasing trend in median HHI, indicating a decrease in portfolio diversification.



**Table 1**

**Summary Statistics**

Table 1 provides summary statistics for the main sample. Panel A summarizes the main variables I use in my paper. *NumPat* is the number of successful patent applications for the firm-year. *PtValue* is the patent value calculated based on the inflation-adjusted market reaction after the issuance. *Citation* is the number of patents weighted by citation. *Q* stands for the firm's Tobin's Q. *Leverage* is liability over total asset. *Cash* is the firm's cash over total asset. *KZ-index* is the Kaplan-Zingales measure of financial constraints. *Tangibility* is property, plant, and equipment over total assets. *Hindex* is the Herfindahl index of the firm's industry. *IO* is the fraction of outstanding stocks owned by the institutional investors. *Diversified IO* is the fraction of outstanding shares owned by institutions with higher diversification; an institution is considered highly diversified if its portfolio HHI is below the annual average. *Orth\_DivIO* is the element in Diversified IO that is orthogonal to the overall IO. *C-index* is a common ownership measure following Lewellen and Lowry (2021). More detailed variable definitions are in the Appendix 1. Panel B shows the interaction between high-diversified institutions, including institution size and the Bushee (1998, 2001) institution types definition.

Panel A: Firm-Level Statistics							
VARIABLES	N	mean	sd	p25	p50	p75	p90
NumPat	168,019	8.147	88.75	0	0	0	5
PtValue (in millions)	168,019	261.0	3,064	0	0	0	31.79
Citation	168,019	17.23	184.7	0	0	0	10.41
R&D/Sales	168,019	0.032	0.088	0	0	0.0263	0.099
Patent/R&D	168,019	0.125	0.437	0	0	0	0.305
Patent/RDC	167,073	0.0452	0.158	0	0	0	0.110
PtValue/R&D	168,019	0.636	2.367	0	0	0	1.225
PtValue/RDC	167,073	0.232	0.864	0	0	0	0.448
Citation/R&D	168,019	0.277	1.039	0	0	0	0.586
Citation/RDC	167,073	0.101	0.382	0	0	0	0.212
Q	151,808	1.878	2.193	1.012	1.296	1.985	3.336
ROA	164,055	0.0506	0.433	0.0207	0.0920	0.155	0.219
Leverage	167,253	0.243	0.268	0.0497	0.195	0.367	0.538
Cash	167,969	0.156	0.195	0.0235	0.0728	0.211	0.443
KZ index	145,611	0.570	2.972	0.0535	0.594	1.278	1.981
Sales (in millions)	168,019	1,898	9,921	35.76	161.6	787.1	3,179
Tangibility	164,132	0.254	0.243	0.0538	0.177	0.385	0.657
Hindex	168,019	0.236	0.188	0.107	0.185	0.313	0.480
InvSize (in millions)	162,133	53.99	102.75	1.63	9.33	64.34	160.39
InvRet	162,133	0.0512	0.1733	-0.0003	0.0047	0.0221	0.0852
IO	168,019	0.383	0.308	0.0993	0.326	0.635	0.854
Diversified IO	168,019	0.309	0.271	0.0688	0.238	0.509	0.731
Orth_DivIO	168,019	-8.68e-10	0.0788	-0.0196	0.0134	0.0345	0.0754
C-Index*10000	168,019	29.28	50.07	2.912	10.69	32.53	79.88

Panel B: Diversified and less diversified Institutions			
	Highly Diversified	Less Diversified	Difference
AUM	6063.40	1063.11	5000.29*** (49.159)
Transient	25.06%	24.66%	0.40%*** (2.666)
Quasi-Indexers	56.20%	38.80%	17.40%*** (103.010)
Dedicated	1.18%	6.83%	-5.64%*** (-84.675)
Non-Classified	17.56%	29.71%	-12.15%*** (-84.116)

**Table 2**

**IO and Innovation: Panel regression results**

Table 2 reports the results of the panel regression  $Innovation_{f,t+n} = \alpha + \beta IO_{f,t} + \gamma X_{f,t} + \theta_f + \lambda_{j,t} + \varepsilon_{f,t}$ , where  $n = 2$  if the dependent variable is one of the innovation output measures, and  $n=0$  if it is an input measure (R&D expenditures). The key independent variable is overall institutional ownership (*IO*). I control for the variables that are correlated with innovations such as *ROA*, *Leverage*, *Cash*, *Tobin's Q*, *KZ-index*, *ln(Sales)*, *Tangibility*, *Hindex*, *C-index*, as well as the firm-fixed effect and the industry-year fixed effect. This table confirms the result in the literature that *IO* is positively associated with innovation.

VARIABLES	(1) ln(1+NumPat <sub>t+2</sub> )	(2) ln(1+PatValue <sub>t+2</sub> )	(3) ln(1+Citation <sub>t+2</sub> )	(4) ln(1+R&D <sub>t</sub> )
IO	0.0577*** (3.821)	0.0955*** (3.451)	0.0825*** (4.429)	0.2333*** (18.597)
ROA	-0.0714*** (-5.449)	-0.0950*** (-4.093)	-0.0775*** (-4.417)	-0.0543 (-1.601)
Leverage	-0.1276*** (-7.608)	-0.2002*** (-7.823)	-0.1650*** (-7.695)	-0.0116 (-0.983)
Cash	0.1536*** (8.070)	0.1835*** (5.626)	0.1970*** (7.993)	0.0096 (0.584)
Q	0.0065*** (5.014)	0.0218*** (8.409)	0.0090*** (5.162)	-0.0053*** (-4.974)
KZ-index	0.0015*** (2.867)	0.0040*** (3.750)	0.0022*** (2.873)	0.0049*** (6.142)
ln(Sales)	0.1192*** (29.871)	0.2018*** (28.070)	0.1273*** (26.637)	0.1857*** (42.316)
Tangibility	0.0559*** (2.752)	0.0468 (1.281)	0.0744*** (2.916)	-0.0700*** (-3.926)
Hindex	0.0399* (1.687)	0.1215*** (2.966)	0.0439 (1.530)	0.0356* (1.890)
C-Index	-0.2849 (-0.387)	-0.5881 (-0.443)	-2.0491** (-2.264)	7.3016*** (12.037)
Constant	-0.1355*** (-5.799)	-0.1816*** (-4.412)	-0.0547* (-1.940)	-0.0361* (-1.667)
Firm FE	YES	YES	YES	YES
Industry x Year FE	YES	YES	YES	YES
Observations	114,577	114,577	114,577	142,836
R-squared	0.839	0.838	0.823	0.936

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1



**Table 3****Double-sorted portfolio comparisons**

Table 3 reports the portfolio average of different variables for the dependent double-sorted portfolios. For each year, I first sort all the firms on *IO* and divide the sample into quintiles. Then for each *IO* quintile, I further sort the firms on *DivIO* and form *DivIO* quintiles within the *IO* portfolio. I then have 25 portfolios for each year from 1980 to 2019. I then calculate the time-series average of different variables. Panel A and B shows the result for *IO* and *DivIO*, while Panel C to E shows the results for different innovation measures.

<b>Panel A: IO</b>					
	<b>IO_Q1</b>	<b>IO_Q2</b>	<b>IO_Q3</b>	<b>IO_Q4</b>	<b>IO_Q5</b>
<b>DivIO_Q1</b>	0.008	0.130	0.320	0.511	0.725
<b>DivIO_Q2</b>	0.012	0.132	0.322	0.515	0.716
<b>DivIO_Q3</b>	0.022	0.153	0.335	0.526	0.735
<b>DivIO_Q4</b>	0.038	0.183	0.368	0.556	0.773
<b>DivIO_Q5</b>	0.056	0.221	0.408	0.597	0.840
<b>Q5-Q1</b>	0.050*** (6.336)	0.091*** (6.322)	0.088*** (3.794)	0.086*** (3.389)	0.115*** (5.816)
<b>Panel B : Diversified IO</b>					
	<b>IO_Q1</b>	<b>IO_Q2</b>	<b>IO_Q3</b>	<b>IO_Q4</b>	<b>IO_Q5</b>
<b>DivIO_Q1</b>	0.001	0.041	0.135	0.274	0.395
<b>DivIO_Q2</b>	0.004	0.084	0.225	0.390	0.548
<b>DivIO_Q3</b>	0.012	0.113	0.272	0.441	0.610
<b>DivIO_Q4</b>	0.028	0.149	0.315	0.485	0.668
<b>DivIO_Q5</b>	0.052	0.200	0.375	0.548	0.762
<b>Q5-Q1</b>	0.051*** (7.370)	0.159*** (14.410)	0.239*** (13.383)	0.273*** (12.813)	0.367*** (19.118)
<b>Panel C: Patent Counts(t+2)</b>					
	<b>IO_Q1</b>	<b>IO_Q2</b>	<b>IO_Q3</b>	<b>IO_Q4</b>	<b>IO_Q5</b>
<b>DivIO_Q1</b>	0.49	0.47	2.82	3.20	8.01
<b>DivIO_Q2</b>	0.35	0.66	11.01	12.54	12.13
<b>DivIO_Q3</b>	1.88	0.99	16.07	19.19	17.34
<b>DivIO_Q4</b>	2.35	1.79	21.70	21.87	15.86
<b>DivIO_Q5</b>	0.84	3.43	15.83	16.41	15.44
<b>Q5-Q1</b>	0.35 (0.712)	2.95*** (3.139)	13.00*** (3.662)	13.21*** (6.660)	7.44*** (4.30)

**Panel D: Citation-Weighted Patent(t+2)**

	<b>IO_Q1</b>	<b>IO_Q2</b>	<b>IO_Q3</b>	<b>IO_Q4</b>	<b>IO_Q5</b>
<b>DivIO_Q1</b>	0.99	1.14	5.92	6.93	16.62
<b>DivIO_Q2</b>	0.69	1.62	22.54	25.95	27.98
<b>DivIO_Q3</b>	3.28	2.40	30.67	39.46	37.73
<b>DivIO_Q4</b>	4.56	3.83	49.12	46.20	33.05
<b>DivIO_Q5</b>	1.87	10.13	32.43	34.14	31.50
<b>Q5-Q1</b>	0.88 (0.909)	8.99*** (2.448)	26.51*** (3.938)	27.21*** (6.558)	14.88*** (4.300)

**Panel E: Innovation Value(t+2)**

	<b>IO_Q1</b>	<b>IO_Q2</b>	<b>IO_Q3</b>	<b>IO_Q4</b>	<b>IO_Q5</b>
<b>DivIO_Q1</b>	7.45	5.67	42.79	167.55	274.29
<b>DivIO_Q2</b>	2.88	9.47	264.75	513.76	511.90
<b>DivIO_Q3</b>	32.89	35.56	554.58	697.10	499.06
<b>DivIO_Q4</b>	37.67	38.57	751.68	714.42	475.03
<b>DivIO_Q5</b>	16.03	123.75	760.83	519.88	376.41
<b>Q5-Q1</b>	8.58 (0.677)	118.08*** (2.986)	718.04*** (5.197)	352.32*** (3.521)	102.12* (1.651)

**Table 4**

**Panel regressions results**

Table 4 reports the results of the panel regression  $Innovation_{f,t+n} = \alpha + \omega Orth\_DivIO_{f,t} + \beta IO_{f,t} + \gamma X_{f,t} + \theta_f + \lambda_{j,t} + \varepsilon_{f,t}$ , where  $n = 2$  if the dependent variable is one of the innovation output measures, and  $n=0$  if it is an input measure (R&D expenditures). The key independent variable is  $Orth\_DivIO_{f,t}$ , which is the orthogonalized component of  $DivIO$  from overall ownership ( $IO$ ). To do the orthogonalization, I run the regression  $DivIO_{f,t} = \alpha + \beta IO_{f,t} + \varepsilon_{f,t}$  and take the error term  $\varepsilon_{f,t}$  as the  $Orth\_DivIO_{f,t}$  measure. I control for the variables that are correlated with innovations such as ROA, Leverage, Cash, Tobin's Q, KZ-index, ln(Sales), Tangibility, Hindex, C-index, as well as the firm-fixed effect and the industry-year fixed effect. The results in Table 4 shows that when controlling for the overall ownership, diversified ownership is positively correlated with innovation.

VARIABLES	(1) ln(1+NumPat <sub>t+2</sub> )	(2) ln(1+PatValue <sub>t+2</sub> )	(3) ln(1+Citation <sub>t+2</sub> )	(4) ln(1+R&D <sub>t</sub> )
Orth_DivIO	0.1976*** (6.195)	0.3831*** (6.613)	0.1975*** (5.027)	0.2696*** (9.529)
IO	0.0741*** (4.831)	0.1273*** (4.506)	0.0989*** (5.231)	0.2581*** (20.145)
ROA	-0.0701*** (-5.339)	-0.0926*** (-3.974)	-0.0762*** (-4.337)	-0.0539 (-1.600)
Leverage	-0.1267*** (-7.619)	-0.1985*** (-7.828)	-0.1641*** (-7.703)	-0.0108 (-0.917)
Cash	0.1551*** (8.159)	0.1866*** (5.723)	0.1986*** (8.061)	0.0113 (0.690)
Q	0.0067*** (5.105)	0.0220*** (8.463)	0.0092*** (5.231)	-0.0052*** (-4.897)
KZ-index	0.0015*** (2.924)	0.0040*** (3.824)	0.0022*** (2.924)	0.0050*** (6.064)
ln(Sales)	0.1181*** (29.664)	0.1997*** (27.795)	0.1262*** (26.440)	0.1842*** (42.052)
Tangibility	0.0560*** (2.755)	-0.0467 (-1.278)	0.0745*** (2.918)	-0.0699*** (-3.920)
Hindex	0.0387 (1.634)	0.1190*** (2.907)	0.0426 (1.486)	0.0340* (1.807)
C-Index_48	-1.7770** (-2.337)	-3.4812** (-2.527)	-3.5407*** (-3.790)	5.1630*** (8.368)
Constant	-0.1331*** (-5.707)	-0.1771*** (-4.305)	-0.0524* (-1.858)	-0.0326 (-1.512)
Firm FE	YES	YES	YES	YES
Industry x Year FE	YES	YES	YES	YES
Observations	114,577	114,577	114,577	142,836
R-squared	0.839	0.838	0.823	0.936

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.10

**Table 5**

**Panel regressions results with interaction**

Table 5 reports the results of the panel regression  $Innovation_{f,t+n} = \alpha + \omega_1 Orth\_DivIO_{f,t} + \omega_2 Orth\_DivIO_{f,t} \times HighIO_{f,t} + \beta IO_{f,t} + \gamma X_{f,t} + \theta_f + \lambda_{j,t} + \varepsilon_{f,t}$ , where  $n = 2$  if the dependent variable is one of the innovation output measures, and  $n=0$  if it is an input measure (R&D/ Sales). The key coefficient is  $\omega_2$ , which indicates whether diversification has different impact when the overall ownership is high. The numbers here do not support this. I control for the variables that are correlated with innovations such as ROA, Leverage, Cash, Tobin's Q, KZ-index, ln(Sales), Tangibility, Hindex, C-index, as well as the firm-fixed effect and the industry-year fixed effect. The results in Table 5 shows that the effect of diversified ownership does not depend on the overall institutional ownership level.

VARIABLES	(1) ln(1+NumPat <sub>t+2</sub> )	(2) ln(1+PatValue <sub>t+2</sub> )	(3) ln(1+Citation <sub>t+2</sub> )	(4) R&D/Sales <sub>t</sub>
Orth_DivIO <sub>t-1</sub>	0.1387** (2.263)	0.2256*** (2.476)	0.1676** (2.085)	0.0959** (2.233)
Orth_DivIO <sub>t-1</sub> x HighIO <sub>t-1</sub>	0.0695 (1.053)	0.1042 (1.386)	0.1062 (1.266)	0.0078 (0.182)
IO <sub>t-1</sub>	0.0730*** (4.750)	0.1226*** (4.326)	0.0973*** (5.130)	0.1652*** (23.209)
ROA <sub>t</sub>	-0.0701*** (-5.337)	-0.0924*** (-3.969)	-0.0762*** (-4.335)	-0.0549 (-1.507)
Leverage <sub>t-1</sub>	-0.1267*** (-7.616)	-0.1983*** (-7.818)	-0.1640*** (-7.698)	0.0142 (1.176)
Cash <sub>t-1</sub>	0.1550*** (8.151)	0.1860*** (5.705)	0.1984*** (8.053)	0.1110*** (8.599)
Q <sub>t-1</sub>	0.0067*** (5.109)	0.0221*** (8.469)	0.0092*** (5.234)	-0.0009 (-0.881)
KZ-index <sub>t-1</sub>	0.0015*** (2.906)	0.0039*** (3.782)	0.0022*** (2.903)	0.0023*** (3.692)
ln(Sales <sub>t-1</sub> )	0.1181*** (29.661)	0.1996*** (27.791)	0.1262*** (26.437)	-0.1409*** (-31.512)
Tangibility <sub>t-1</sub>	0.0561*** (2.758)	-0.0464 (-1.272)	0.0746*** (2.921)	0.0566*** (5.352)
Hindex <sub>t-1</sub>	0.0386 (1.631)	0.1188*** (2.901)	0.0425 (1.483)	0.0029 (0.407)
C-Index <sub>t-1</sub>	-1.7555** (-2.309)	-3.3872** (-2.458)	-3.5079*** (-3.753)	-0.8214* (-1.903)
Constant	-0.1326*** (-5.681)	-0.1748*** (-4.248)	-0.0516* (-1.829)	0.7410*** (37.562)
Firm FE	YES	YES	YES	YES
Industry x Year FE	YES	YES	YES	YES
Observations	114,577	114,577	114,577	142,836
R-squared	0.839	0.838	0.823	0.805

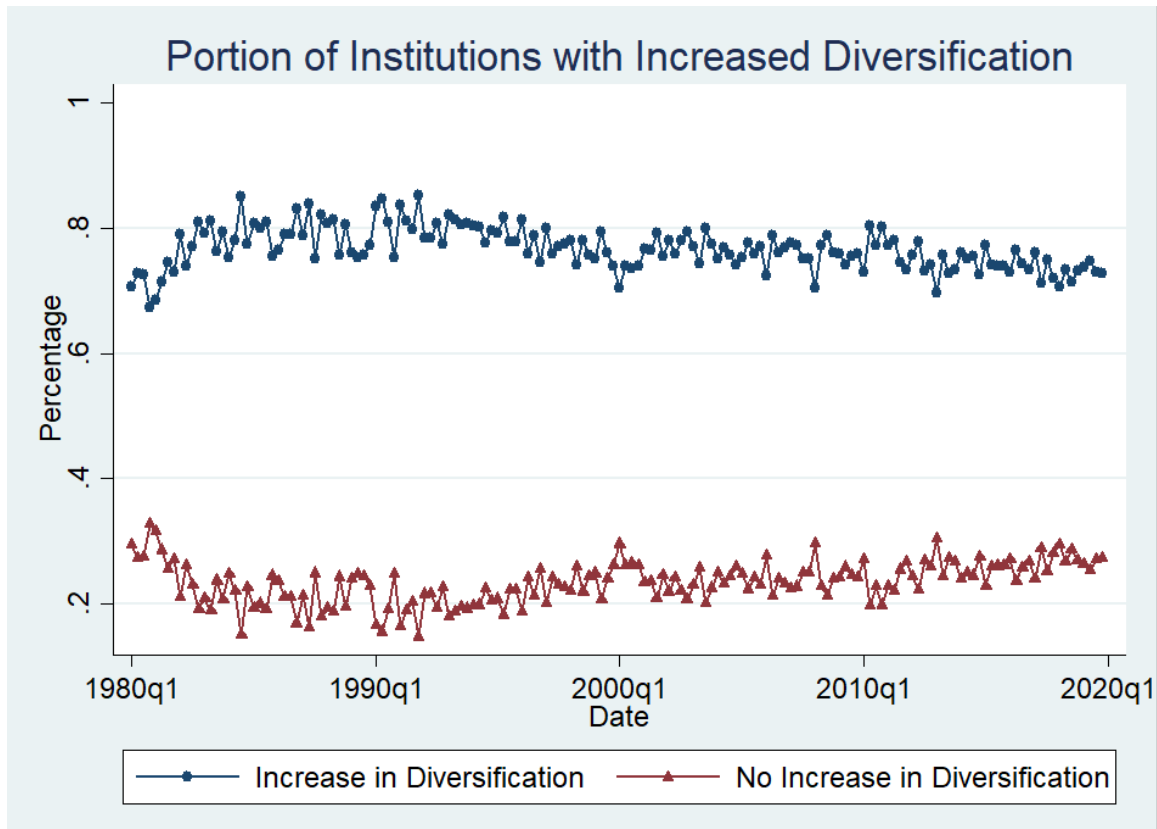
Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.10

**Figure 2**

**Portion of institutions with increased Diversification after the simulated mergers**

Figure 2 shows the portion of institutions with increased diversification after the hypothetical mergers in my simulation. To perform the simulation, for each quarter, I randomly select 50 institutions from the 13F institutional holding database and conduct pair-wise hypothetical mergers across all possible institution-pairs among the 50 institutions. I then calculate the portion of institutions with a drop in HHI after the merger. I do an independent draw of 50 institutions for each quarter. The result supports my conjecture that mergers are likely to increase portfolio diversification for the involved institutions.



**Table 6****Simulated merger sample and actual mergers**

Table 6 provides additional information for the simulated merger sample as well as the actual mergers. Panel A shows the total number of institutions in each quarter that I draw from. Panel B shows that the institutions drawn in the simulation sample have similar level and standard errors of diversification as the overall sample. Panel C shows that the increase in diversification after the merger is statistically significant for the simulated sample. Panel D shows the same for the actual mergers in my sample. 65.08% of the involved institutions in the actual mergers increase their diversification after the mergers, and the increase is statistically significant.

**Panel A: Number of Total Institutions in Each Quarter**

<b>Average</b>	<b>min</b>	<b>Max</b>
2149.08	525	5616

**Panel B: Comparison Between All Institutions and Merger Samples**

	<b>Mean</b>	<b>Median</b>	<b>Std</b>
<b>All Institutions (1-HHI)</b>	0.8260	0.9112	0.2119
<b>Simulation Sample (1-HHI)</b>	0.8464	0.9172	0.1924
<b>All Institutions (1/HHI)</b>	10.8149	11.2658	5.7189
<b>Simulation Sample (1/HHI)</b>	11.5688	12.0726	5.6780

**Panel C: Changes Before/After the Merger (Simulated Sample)**

<b>Simulated Change in 1-HHI</b>	0.0490*** (180.58)	0.0087	0.1700
<b>Simulated Change in 1/HHI</b>	2.0647*** (262.48)	1.2794	4.9246

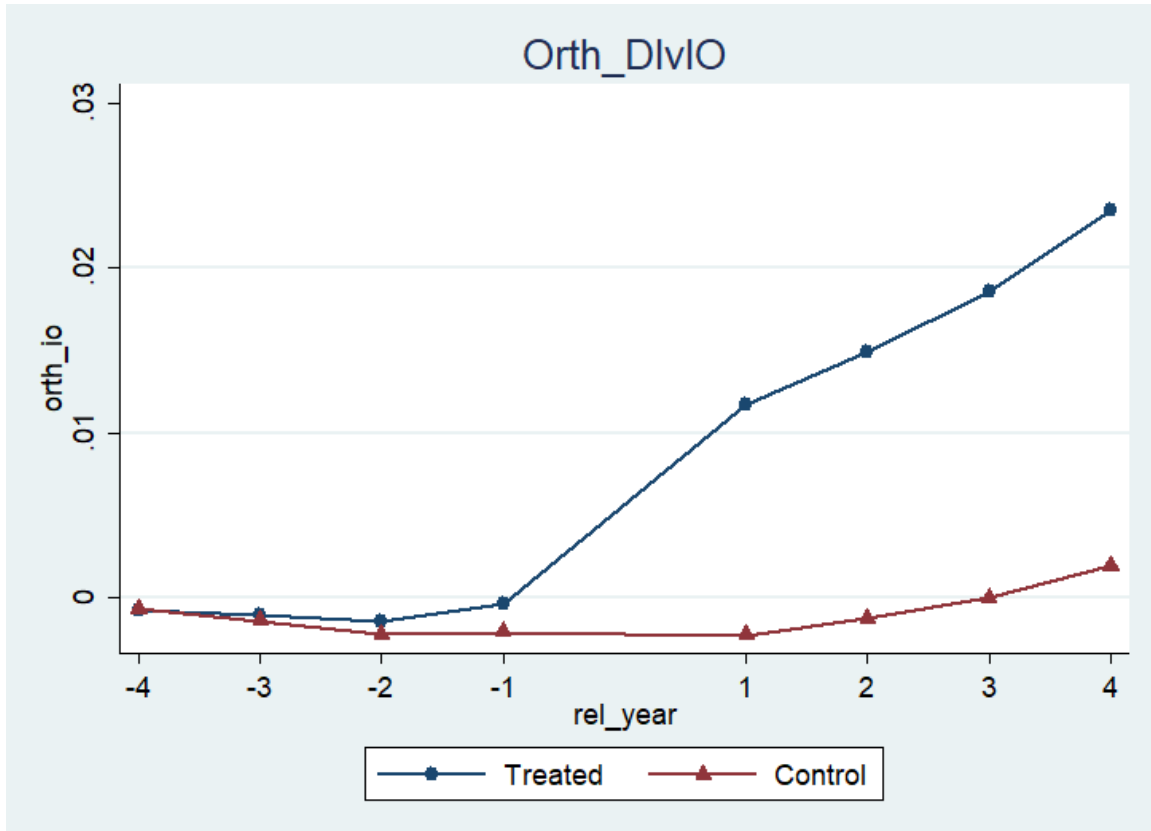
**Panel D: Changes Before/After the Merger (Actual Merger Sample)**

<b>Percentage of Institutions with a decrease in HHI</b>	65.08%
<b>Change in 1-HHI</b>	0.0104*** (1.999)
<b>Change in 1/HHI</b>	1.2987*** (3.635)

**Figure 3**

**Trend for Orthogonalized DivIO around mergers**

Figure 3 shows the trend for orthogonalized *DivIO* around the merger years for the treated and control groups. To do the orthogonalization, I run the regression  $DivIO_{f,t} = \alpha + \beta IO_{f,t} + \varepsilon_{f,t}$  and take the error term  $\varepsilon_{f,t}$  as the  $Orth\_DivIO_{f,t}$  measure. Treated firms are defined as the firms held by one of the merging institutions before the mergers, and the control firms are those that are not held by either of the firms. Figure 3 shows that the level and trend of  $Orth\_DivIO_{f,t}$  are similar before the mergers, and there is a much larger spike after the mergers for the treated firms.



**Table 7**

**The DID test results on diversified ownership (DivIO) around mergers**

Table 7 reports the results of the DID test on diversified ownership. *Treated firms* are those held by one of the merging institutions before the mergers, and *control firms* are those that are not held by either of the firms. The event window is three years before and three years after the mergers. The dependent variable is the diversified ownership measure *Orth\_DivIO*. The key coefficient of interest is that for the interaction term *Treated x Post*. *Q* is the Tobin's Q, and *MVE* is the total value of equity. The results in this table confirm that diversified ownership increases after the mergers for the treated firms. Columns 1 and 2 report the results with and without control variables. Column 3 reports the result excluding mergers from 1997 to 2003, and column 4 reports the DID test in a dynamic panel setting.

VARIABLES	(1) Orth_DivIO	(2) Orth_DivIO	(3) Orth_DivIO (Exclude 1997-2003)	(4) Orth_DivIO
Treated	-0.0003* (-1.714)	0.0000 (0.120)	0.0012*** (5.439)	0.0001 (0.458)
Post	0.0027*** (27.373)	0.0028*** (26.143)	0.0009*** (7.330)	
Treated x Post	0.0110*** (52.257)	0.0106*** (46.618)	0.0105*** (37.886)	
Pre2 x Treated				-0.0002 (-0.577)
Pre1 x Treated				0.0002 (0.859)
Post1 x Treated				0.0093*** (32.151)
Post2 x Treated				0.0105*** (33.927)
Post3 x Treated				0.0120*** (35.851)
ROA <sub>t</sub>		-0.0018*** (-5.535)	-0.0045*** (-10.244)	-0.0019*** (-5.523)
Q <sub>t</sub>		-0.0016*** (-31.820)	-0.0010*** (-19.452)	-0.0016*** (-31.986)
ln(MVE <sub>t</sub> )		-0.0000 (-0.135)	0.0007*** (8.243)	0.0000*** (24.131)
Constant	-0.0070*** (-98.787)	-0.0020*** (-28.920)	0.0009** (2.262)	0.0021*** (14.649)
Firm FE	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES
Period Dummies	NO	NO	NO	YES
Observations	1,336,558	1,336,558	795,515	1,149,976
R-squared	0.528	0.528	0.538	0.525

Robust t-statistics in parentheses

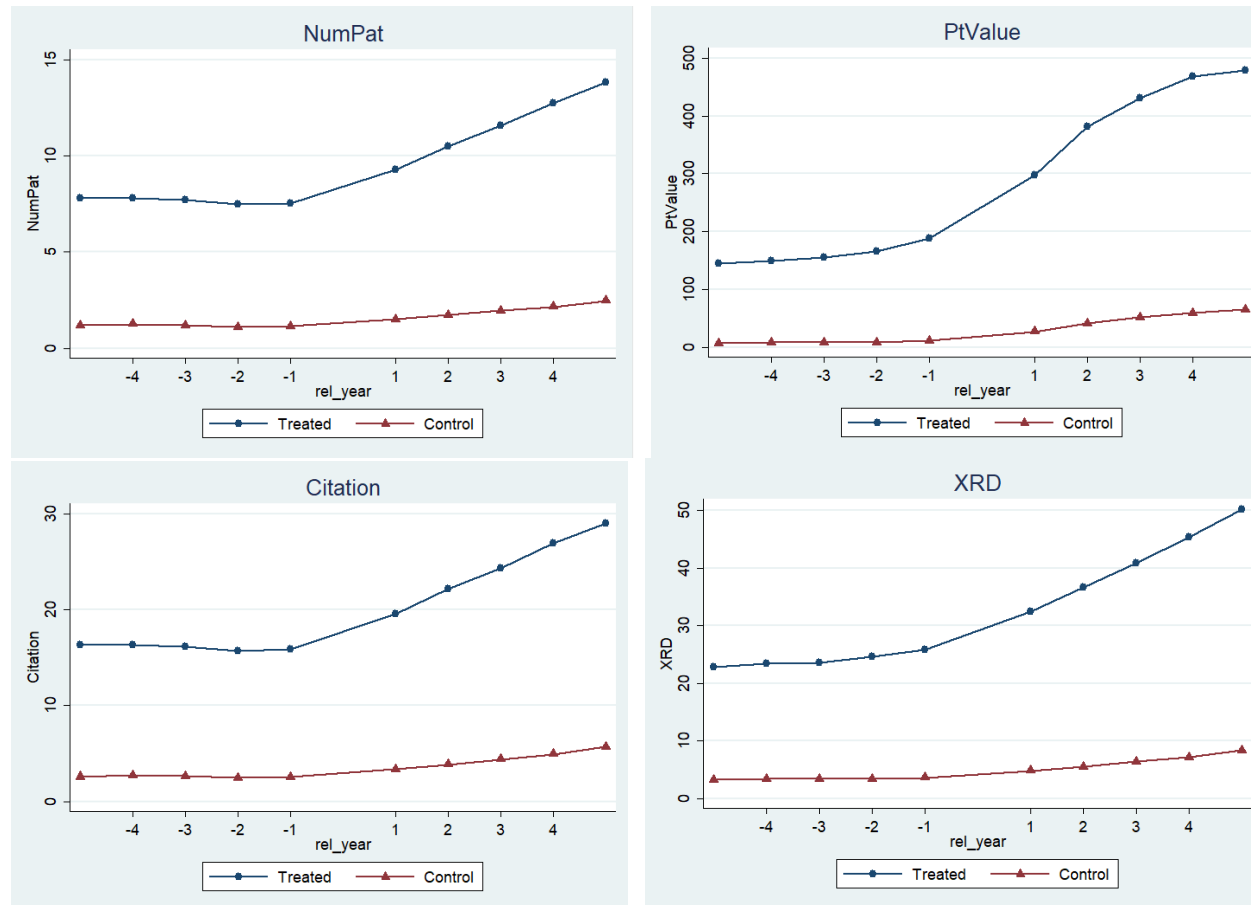
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Figure 4

### Trend of Innovation Around Mergers

Figure 4 shows the trend of the innovation measures for the treated firms and control firms. *Treated firms* are those held by one of the merging institutions before the mergers, and *control firms* are those that are not held by either of the firms. *NumPat* is the number of successful patent applications for the firm-year. *PtValue* is the patent value calculated based on market reaction after the issuance. *Citation* is the number of patents weighted by Citation, and *XRD* is the R&D expenditures. The figures show parallel trend of innovation before the mergers and a spike for the treated firms after the merger.



**Table 8**  
**DID regression result on Innovation**

Table 8 reports the results of the DID regression:  $Innovation_{m,f,t} = \alpha + \beta Treated_{m,f} + \gamma Post_{m,t} + \delta Treated_{m,f} \times Post_{m,t} + X_{f,t} + \theta_f + \omega_m + \varepsilon_{m,f,t}$ . The event window is 3 years before and 3year after the mergers. The dependent variables are innovation input and output measures. Treated firms are those held by one of the merging institutions before the mergers, and the control firms are those that are held by neither of the firms. The key coefficient of interest is that for the interaction term  $Treated \times Post$ . Control variables include overall institutional ownership, ROA, firm leverage, Cash/Total Asset, Tobin's Q, Kaplan-Zingales financial constraint index, ln(Sales), Hindex, average investor size, investor performances, common ownership measure (C-index), and institutional investor size and performances.

VARIABLES	(1) ln(1+NumPat)	(2) ln(1+PatValue)	(3) ln(1+Citation)	(4) R&D/Sales <sub>t</sub>
Treated	0.0194*** (12.844)	0.0444*** (16.584)	0.0244*** (12.305)	0.0051*** (11.541)
Post	0.0085*** (8.412)	0.0152*** (10.513)	0.0028*** (2.401)	0.0112*** (26.399)
Treated x Post	0.0061** (2.049)	0.0094*** (2.513)	0.0033 (1.318)	-0.0001 (-0.171)
IO <sub>t-1</sub>	0.0787*** (16.506)	0.1957*** (23.514)	0.0980*** (15.808)	0.0685*** (43.171)
ROA <sub>t</sub>	-0.0125*** (-4.081)	-0.0059** (-2.111)	-0.0138*** (-4.005)	-0.0341*** (-4.152)
Leverage <sub>t-1</sub>	-0.0549*** (-16.982)	-0.1202*** (-26.135)	-0.0701*** (-16.899)	-0.0166*** (-6.091)
Cash <sub>t-1</sub>	0.1655*** (32.254)	0.2499*** (29.780)	0.2395*** (33.883)	0.0875*** (32.477)
Q <sub>t-1</sub>	0.0039*** (10.982)	0.0282*** (34.608)	0.0054*** (10.072)	0.0007*** (2.994)
KZ-index <sub>t-1</sub>	0.0010*** (4.852)	0.0020*** (5.205)	0.0018*** (6.218)	0.0014*** (7.511)
ln(Sales <sub>t-1</sub> )	0.0889*** (85.709)	0.1760*** (96.080)	0.1011*** (76.533)	0.0783*** (79.932)
Tangibility <sub>t-1</sub>	0.1176*** (22.541)	0.0620*** (6.950)	0.1522*** (22.137)	0.0579*** (25.590)
Hindex <sub>t-1</sub>	0.0041 (0.646)	0.0277*** (2.592)	0.0101* (1.792)	0.0090*** (5.418)
C-Index <sub>t-1</sub>	-1.4115*** (-6.839)	-2.3044*** (-6.180)	-1.6925*** (-6.695)	-0.4653*** (-8.088)
Inv_Size <sub>t-1</sub>	-0.0001 (-0.344)	0.0036*** (5.887)	0.0011** (1.969)	0.0071*** (32.237)
Inv_Ret <sub>t</sub>	-0.0012 (-0.284)	0.0107 (1.357)	-0.0066 (-1.217)	-0.0014 (-1.475)
Constant	-0.0638*** (-12.280)	-0.2940*** (-29.311)	-0.0395*** (-5.208)	0.3372*** (95.406)
Firm FE	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES
Observations	1,116,595	1,116,595	1,116,595	1,116,595
R-squared	0.806	0.814	0.786	0.187

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 9**  
**DID Test on Innovation efficiency**

Table 9 reports the results of the DID regression on innovation efficiency:  $Efficiency_{m,f,t} = \alpha + \beta Treated_{m,f} + \gamma Post_{m,t} + \delta Treated_{m,f} \times Post_{m,t} + X_{f,t} + \theta_f + \omega_m + \varepsilon_{m,f,t}$ . The event window is 3 years before and 3 years after the mergers. The dependent variables are innovation efficiency measures. Treated firms are those held by one of the merging institutions before the mergers, and the control firms are those held by neither of the merging institutions. The key coefficient of interest is that for the interaction term  $Treated \times Post$ . Control variables include overall institutional ownership, ROA, firm leverage, Cash/Total Asset, Tobin's Q, Kaplan-Zingales financial constraint index, ln(Sales), Hindex, average investor size, investor performances, common ownership measure (C-index), and institutional investor size and performances.

VARIABLES	(1) Citation/R&D	(2) Citation/RDC	(3) PatValue/R&D	(4) PatValue/RDC
Treated	-0.0161 (-1.231)	-0.0040 (-0.602)	0.0182 (1.291)	0.0105 (1.176)
Post	-0.1485*** (-9.255)	-0.0491*** (-7.823)	0.1095*** (10.435)	0.0522*** (8.560)
Treated x Post	0.0702*** (4.039)	0.0423*** (5.418)	0.0531** (2.237)	0.0499*** (4.308)
IO <sub>t-1</sub>	-0.0304 (-0.625)	0.0354 (1.573)	0.0513 (0.944)	0.0396 (1.294)
ROA <sub>t</sub>	0.0641*** (4.026)	0.0358*** (4.115)	0.1196*** (6.148)	0.0558*** (5.739)
Leverage <sub>t-1</sub>	-0.1670*** (-3.712)	-0.1496*** (-8.493)	-0.4326*** (-17.367)	-0.1855*** (-14.326)
Cash <sub>t-1</sub>	0.0075 (0.079)	0.1453*** (3.999)	0.0788 (1.233)	0.0158 (0.529)
Q <sub>t-1</sub>	0.0174*** (2.862)	0.0067*** (2.747)	0.1929*** (24.417)	0.0781*** (21.655)
KZ-index <sub>t-1</sub>	-0.0065*** (-4.399)	-0.0011 (-1.386)	-0.0029* (-1.655)	-0.0063*** (-4.750)
ln(Sales <sub>t-1</sub> )	-0.2773*** (-11.970)	-0.1205*** (-11.960)	0.1156*** (8.275)	0.0225*** (2.828)
Tangibility <sub>t-1</sub>	-0.6737*** (-4.757)	-0.2512*** (-6.214)	0.0845 (1.194)	-0.0291 (-0.590)
Hindex <sub>t-1</sub>	0.6193*** (8.306)	0.3299*** (9.026)	0.6088*** (10.192)	0.2314*** (6.541)
C-Index <sub>t-1</sub>	11.0573*** (11.078)	4.0854*** (10.014)	-14.5130*** (-7.703)	-6.4884*** (-7.541)
Inv_Size <sub>t-1</sub>	0.0298*** (3.983)	0.0345*** (7.914)	0.0265*** (5.904)	0.0044* (1.652)
Inv_Ret <sub>t</sub>	0.2788*** (8.974)	0.0840*** (9.349)	0.1426*** (2.739)	0.0589*** (2.613)
Constant	2.2841*** (15.326)	1.0941*** (16.341)	-0.4404*** (-5.469)	-0.0042 (-0.077)
Firm FE	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES
Observations	1,116,595	1,116,595	1,116,595	1,116,595
R-squared	0.806	0.814	0.786	0.187

Robust t-statistics in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 10****Dynamic DID regression result**

Table 9 reports the results of the DID tests in a dynamic setting. In this test, I include different dummies for each year around the merger years. Pre2 is the dummy for year -2 prior to the mergers, Pre1 is the dummy for year -1 prior to the mergers, Post1, Post 2, Post 3 are for year +1, +2, +3, respectively. Treated firms are those held by one of the merging institutions before the mergers, and the control firms are those not held by either of the merging institutions. Control variables include overall institutional ownership, ROA, firm leverage, Cash/Total Asset, Tobin's Q, Kaplan-Zingales financial constraint index, ln(Sales), Hindex, and common ownership measure (C-index). This table shows there is parallel trend for innovation before the mergers, and the difference in innovation measures between the treated and controls is increasing in the years following the mergers.

VARIABLES	(1) ln(1+NumPat)	(2) ln(1+PatValue)	(3) ln(1+Citation)	(4) PatValue /RDC
Treated	0.0121*** (5.012)	0.0331*** (7.744)	0.0173*** (5.534)	0.0106* (1.798)
Pre2 x Treated	0.0025 (1.094)	0.0032 (0.780)	0.0019 (0.640)	0.0036* (1.780)
Pre1 x Treated	0.0041* (1.803)	0.0045 (1.109)	0.0035 (1.187)	0.0029 (1.408)
Post1 x Treated	0.0047* (1.864)	0.0135*** (2.933)	0.0001 (0.0311)	0.0374*** (16.584)
Post2 x Treated	0.0079*** (2.944)	0.0140*** (2.839)	0.0031 (0.9057)	0.0456*** (18.794)
Post3 x Treated	0.0151*** (5.175)	0.0227*** (4.244)	0.0091*** (2.487)	0.0470*** (17.664)
Pre2	0.0019 (1.488)	0.0026 (1.317)	0.0005 (0.289)	0.0001 (0.095)
Pre1	0.0008 (0.887)	0.0041** (2.047)	0.0011 (0.631)	0.0015 (1.338)
Post1	0.0076*** (5.403)	0.0081*** (3.676)	0.0039* (1.864)	0.0089*** (6.603)
Post2	0.0074*** (5.972)	0.0084*** (3.612)	0.0032* (1.831)	0.0095*** (7.112)
Post3	0.0095*** (6.487)	0.0082*** (3.821)	0.0036* (1.861)	0.0099*** (7.235)
Firm-Level Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES
Observations	1,146,319	1,146,319	1,146,319	1,146,319
R-squared	0.806	0.814	0.785	0.926

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 11**

**Robustness Tests**

Table 11 reports the key coefficients for different robustness tests. Panel A reports the interaction terms for DID tests with a matched sample. The match is 1-1 non-replacement and based on Mahalanobis distance. Matching metrics includes all control variables in the main DID tests. Panel B reports the results when excluding mergers between 1997 and 2003. Panel C to Panel E repeats the DID tests with a gap imposed between the pre- and post-periods. Also, for Panel B to D, I use the two-year forward measures if the dependent variable is an innovation output measures. Panel B extend the pre-period up to 5 years before the mergers but drop the observations in years -1 and -2. The tests reported in Panel C and Panel D drop the observations in year -1 and +1 and include different number of years around the mergers. The coefficients are qualitatively similar to that of the main DID tests.

Panel F reports the 2SLS panel regression that uses the dummy variable “*Event*” as the first-stage instrument variable. *Event* =1 if the firm is identified as the treated firm and is in the post-merger period for at least one of the merger events in my sample. First stage regression regresses *Orth\_DivIO* on *Event*, and the second stage regresses innovation measures on the fitted *Orth\_DivIO* in the first stage. All firm-level control variables used in the main analyses are also included.

VARIABLES	(1) ln(1+NumPat <sub>t+i</sub> )	(2) ln(1+PatValue <sub>t+i</sub> )	(3) ln(1+Citation <sub>t+i</sub> )	(4) PatValue /RDC
<b>Panel A: Matched Sample (i=0)</b>				
Treated x Post	0.0029** (1.982)	0.0173*** (11.457)	0.0003 (0.215)	0.0396*** (4.984)
Observations	746,970	746,970	746,970	746,970
<b>Panel B: Exclude Mergers From 1997-2003 (i=0)</b>				
Treated x Post	0.0052** (2.142)	0.0299*** (6.607)	0.0049 (1.525)	0.0394*** (3.617)
Observations	768,021	768,021	768,021	768,021
<b>Panel C: Dropping -2 and -1 year (-5 to +3 window, with i=2)</b>				
Treated x Post	0.0082*** (3.780)	0.0081** (2.205)	0.0050* (1.773)	
Observations	913,883	913,883	913,883	
<b>Panel D: Dropping -1 to +1 year (-3 to +3 window, with i=2)</b>				
Treated x Post	0.0073*** (2.736)	0.0097* (1.952)	0.0080* (1.786)	
Observations	639,056	639,056	639,056	
<b>Panel E: Dropping -1 to +1 year (-4 to +4 window, with i=2)</b>				
Treated x Post	0.0066** (2.932)	0.0079*** (2.184)	0.0102*** (3.119)	
Observations	926,436	926,436	926,436	
Firm-Level Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES

VARIABLES	(1) ln(1+NumPat <sub>t+i</sub> )	(2) ln(1+PatValue <sub>t+i</sub> )	(3) ln(1+Citation <sub>t+i</sub> )	(4) PatValue /RDC
<b>Panel F: IV Regression Using “Treated” as the Instrument (i=2)</b>				
Event(First-Stage)		0.0050*** (9.484)		
F-Stats		76.076		
Orth_DivIO (Second-Stage)	1.1942 (0.753)	1.2999 (0.462)	1.6260 (0.816)	1.7132 (0.959)
Observations	107,705	107,705	107,705	107,705
Firm-Level Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES
Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1				

**Table 12****DID Test on Diversification for different groups**

Table 12 reports the DID tests on the diversification measure *Orth\_DivIO* for different subsamples. Column 1 and column 3 show results for the treated firms held by a merging institution whose diversification actually increased after the mergers; columns 2 and 4 show results for treated firms held by a merging institution whose diversification did not increase. The results show that the positive effects are more pronounced in the treated firms whose investor experiences an actual increase in diversification after the mergers.

VARIABLES	(1) Orth_DivIO (Increase = 1)	(2) Orth_DivIO (Increase = 0)	(3) Orth_DivIO (Increase = 1)	(4) Orth_DivIO (Increase = 0)
Treated	0.0001 (0.381)	0.0015*** (7.410)	0.0005** (1.976)	0.0020*** (9.002)
Post	0.0023*** (24.020)	0.0023*** (23.973)	0.0028*** (26.114)	0.0027*** (24.970)
Treated x Post	0.0134*** (43.522)	0.0005* (1.8765)	0.0130*** (39.308)	0.0005* (1.941)
ROA <sub>t</sub>			-0.0018*** (-5.074)	-0.0017*** (-5.425)
Q <sub>t</sub>			-0.0015*** (-28.419)	-0.0015*** (-29.085)
ln(MVE <sub>t</sub> )			-0.0011*** (-14.631)	-0.0007*** (-9.638)
Constant	-0.0027*** (-42.626)	-0.0023*** (-34.945)	0.0068*** (20.610)	0.0056*** (16.836)
Observations	1,252,441	1,160,791	1,252,441	1,160,791
R-squared	0.512	0.522	0.517	0.529

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 13**

**DID tests for institutions with/without diversification increase**

Table 13 reports the DID tests for different subsamples. Columns 1, 3, 5, and 7 show results for treated firms held by a merging institution whose diversification increased post-merger, while columns 2, 4, 6, and 8 show results for treated firms held by a merging institution whose diversification did not increase. For innovation outputs (column 1-6), the results show that the positive effects are concentrated in the treated firms whose investor experiences an actual increase in diversification after the mergers. On the efficiency side, the positive effects also concentrate in the same group of firms. The non-increase group only shows marginally significant effect. The results indicate that innovation outputs and efficiency only improve for the firms with increased diversified ownership.

VARIABLES	(1) ln(1+NumPat) Increase = 1	(2) ln(1+NumPat) Increase = 0	(3) ln(1+PatValue) Increase = 1	(4) ln(1+PatValue) Increase = 0	(5) ln(1+Citation) Increase = 1	(6) ln(1+Citation) Increase = 0	(7) PatValue /RDC Increase = 0	(8) PatValue /RDC Increase = 0
Treated	0.0250*** (11.680)	0.0233*** (12.172)	0.0587*** (15.155)	0.0542*** (16.140)	0.0304*** (10.981)	0.0283*** (11.344)	-0.0027 (-0.311)	0.0002 (0.023)
Post	0.0072*** (8.001)	0.0084*** (10.479)	0.0061*** (5.036)	0.0038*** (3.272)	0.0095*** (7.975)	0.0039*** (2.522)	0.0706*** (10.814)	0.0706*** (10.930)
Treated x Post	0.0150*** (5.030)	-0.0023 (-0.916)	0.0189*** (3.418)	0.0041 (0.905)	0.0093** (2.480)	-0.0068* (-1.691)	0.0746*** (6.885)	0.0158* (1.668)
Firm-level Controls	YES	YES	YES	YES	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	962,546	827,033	962,546	827,033	962,546	827,033	962,546	827,033
R-squared	0.771	0.789	0.788	0.802	0.749	0.767	0.919	0.923



**Table 14****Changes of Institution Types around Merger**

Table 14 summarizes for the merging institutions the change of Bushee's institution types before and after mergers. TRA stands for transient institutions. QIX stands for quasi-indexers. DED stands for dedicated institutions. "TRA to DED", for example, indicates the institution was transient before the mergers, but changes to dedicated institution after the mergers etc.

	Number of Merging Institutions	Percentage	Number of Treated Firms	Percentage
TRA to DED	0	0%	0	0%
QIX to DED	4	3%	2,091	3%
DED to TRA	3	2%	1,350	2%
DED to QIX	4	3%	393	1%
TRA to QIX	15	12%	2,479	3%
QIX to TRA	15	12%	7,688	11%
Remain TRA	8	6%	3,185	4%
Remain QIX	63	49%	45,303	64%
Remain DED	6	5%	4,216	6%
Unidentified	10	8%	4,466	6%
Total	128	100%	71,171	100%

**Table 15**

**DID results with different institution types**

Panel A to C in this table report the DID results for 3 different subsamples of treated firms held by the merging institution whose institution type does not change before and after the merger. Panel D reports the results after excluding the treated firms held by the institutions that change from DED before the mergers to QIX or TRA after the mergers. The results show that the positive effect on innovation exists when the types of the merging institutions do not change or when excluding the institutions type changes that are likely corresponding to an increase in diversification.

<b>Panel A: Subsample – Remain Dedicated</b>				
VARIABLES	(1) ln(1+NumPat)	(2) ln(1+PatValue)	(3) ln(1+Citation)	(4) PatValue /RDC
Treated	0.0140*** (2.759)	0.0805*** (9.101)	0.0182*** (2.622)	0.0084 (0.495)
Post	0.0146*** (15.440)	0.0242*** (17.555)	0.0276*** (21.152)	0.0472*** (7.183)
Treated x Post	0.0172** (2.442)	0.0262*** (2.001)	0.0201** (2.175)	0.0502*** (2.927)
Observations	818,810	818,810	818,810	818,810
<b>Panel B: Subsample – Remain Quasi-Indexer</b>				
Treated	0.0235*** (12.735)	0.0449*** (13.947)	0.0282*** (11.777)	-0.0033 (-0.415)
Post	0.0190*** (19.979)	0.0180*** (12.590)	0.0326*** (25.116)	0.0491*** (7.753)
Treated x Post	-0.0016 (-0.648)	0.0072 (1.624)	-0.0097*** (-3.156)	0.0106 (1.594)
Observations	1,001,403	1,001,403	1,001,403	1,001,403
<b>Panel C: Subsample – Remain Transient</b>				
Treated	0.0277*** (4.833)	0.1154*** (10.065)	0.0304*** (4.100)	0.0301 (1.087)
Post	0.0148*** (15.548)	0.0242*** (17.488)	0.0278*** (21.268)	0.0470*** (7.172)
Treated x Post	0.0363*** (4.058)	0.0406*** (4.010)	0.0418*** (3.721)	0.0410** (1.991)
Observations	816,069	816,069	816,069	816,069
<b>Panel D: Subsample – Exclude DED to QIX and DED to TRA</b>				
Treated	0.0194*** (12.724)	0.0444*** (16.584)	0.0244*** (12.305)	-0.0040 (-0.602)
Post	0.0207*** (21.665)	0.0152*** (10.513)	0.0346*** (26.660)	0.0491*** (7.823)
Treated x Post	0.0058** (2.293)	0.0075** (2.079)	0.0033 (1.318)	0.0423*** (5.418)
Observations	1,116,595	1,116,595	1,116,595	1,116,595
Firm-level Controls	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

**Table 16**

**Subsample Tests for Firms with High vs. Low Industry Relationship**

Table 16 reports the DID tests for different subsamples. Columns 1, 3, 5, and 7 show the results for the *Related* group, while columns 2, 4, 6, and 8 are the results for the *Non-Related* group. Industry relation is measured based on Hoberg and Phillips (2010) TNCI definition. *Related* group consists of the treated firms that has at least 1 TNCI industry peer in the other merging institution's portfolio, while the *Non-Related* group consists of the treated firms with no TNCI industry peer in the other merging institution's portfolio. The results show that the positive effect on innovation outputs and efficiency is more pronounced for the *Related* group and is consistent with the information complementarity hypothesis.

VARIABLES	(1) ln(1+NumPat) Related	(2) ln(1+NumPat) Non-Related	(3) ln(1+PatValue) Related	(4) ln(1+PatValue) Non-Related	(5) ln(1+Citation) Related	(6) ln(1+Citation) Non-Related	(7) PatValue /RDC Related	(8) PatValue /RDC Non-Related
Treated	0.0202*** (7.208)	0.0161*** (9.174)	0.0453*** (8.634)	0.0289*** (9.293)	0.0242*** (6.531)	0.0202*** (8.802)	0.0045 (0.561)	-0.0006 (-0.071)
Post	0.0073*** (4.806)	0.0089*** (4.996)	0.0162*** (5.618)	0.0118*** (5.343)	0.0059*** (3.291)	0.0093*** (6.654)	0.0713*** (10.940)	0.0700*** (10.841)
Treated x Post	0.0232*** (5.253)	-0.0052** (-2.130)	0.0185** (2.157)	-0.0011 (-0.234)	0.0139** (2.557)	-0.0105*** (-3.420)	0.0722*** (7.283)	0.0051 (0.612)
Firm-level Controls	YES	YES	YES	YES	YES	YES	YES	YES
Merger FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	727,477	861,239	727,477	861,239	727,477	861,239	727,477	861,239
R-squared	0.787	0.810	0.805	0.820	0.765	0.787	0.934	0.935

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## Appendix 1: Variable Definitions

VARIABLES	Definition
<b>Ownership Measures</b>	
<i>IO</i>	<i>Institutional Ownership</i> : The fraction of outstanding shares of the firm owned by institutional investors.
<i>DivIO</i>	<i>Diversified Institutional Ownership</i> : The fraction of outstanding shares of the firm owned by a highly diversified institution; an institution is defined as <i>highly diversified</i> if its portfolio HHI is below the median of all institutions that year.
<i>Orth_DivIO</i>	<i>Orthogonalized Diversified Institutional Ownership</i> : The error term of the regression $DivIO_{f,t} = \alpha + \beta IO_{f,t} + \varepsilon_{f,t}$ .
<b>Innovation Measures</b>	
<i>NumPat</i>	<i>Number of Patents</i> : The total number of successful patent applications in a year.
<i>PtValue</i>	<i>Patent Value</i> : The total monetary value of the patents filed in the year. Monetary value is measured by the stock market reaction in a two-day window after the patent is granted.
<i>Citation</i>	<i>Citation-Weighted Patents</i> : The total number of citations received by the patents applied in the year, adjusted for the truncation issue. Specifically, for each quarter, $Citation_{f,q} = \sum_{k \in P_{f,q}} (1 + \frac{C_k}{\bar{C}_q})$ , where $C_k$ is the citation received by patent $k$ , and $\bar{C}_q$ is the average number of citations received by all patents issued in quarter $q$ . The measure is then aggregated at annual level.
<i>XRD/Sales</i>	<i>R&amp;D Expenditures over total sales</i> .
<i>RDC (R&amp;D Capital)</i>	$R\&D(Expense)_t + 0.8R\&D_{t-1} + 0.6R\&D_{t-2} + 0.4R\&D_{t-3} + 0.2R\&D_{t-4}$
<b>Firm-level Variables</b>	
<i>Q</i>	<i>Tobin's Q</i> : (MV of Equity + Book Value of Asset – Book Value of Equity)/Total Assets
<i>ROA</i>	<i>Return on Assets</i> : Operating Income/Total Assets
<i>MVE</i>	<i>Total Value of Equity</i> : Price*Outstanding Shares
<i>Leverage</i>	Total Liability/Total Assets
<i>Cash</i>	<i>Cash/Total Assets</i>
<i>KZ-Index</i>	<i>Kaplan-Zingales Index</i> : Calculated as $-1.002 * \text{Cashflow} + 0.283 * Q + 3.139 * \text{Leverage} - 39.368 * \text{Dividend} - 1.315 * \text{Cash}$
<i>Sales</i>	Firm sales for the year
<i>Tangibility</i>	Property, plant, and equipment/Total Assets
<i>Hindex</i>	HHI of the industry that the firm is in (FF-48). For firm $f$ in industry $J$ , $HHI_f = \sum_{j \in J} w_j$ , where $w_j = Sales_j / \sum_{i \in J} Sales_i$
<i>C-Index</i>	Common ownership measure by Lewellen and Lowry (2021). I first calculate the firm-pair level C-index. For each firm $j$ and $k$ , $C - Index_{j,k} = \sum_{i=1}^N \mu_{i,j} * \mu_{i,k}$ , where $\mu_{i,j}$ ( $\mu_{i,k}$ ) equals to the ownership percentage of investor $i$ in firm $j$ ( $k$ ).

	Next, the firm-level C-index for firm $f$ is the average of the pair-level C-index with all other firms that shares the same industry with firm $f$ .
<i>InvSize</i>	The average AUM (millions) of the institutional investors holding the firm.
<i>InvRet</i>	Average year-to-year return for the firm's institutional investors.

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## Appendix 2:

### Regression with portfolio quintiles

Appendix 2 reports the regression results with different DivIO quintiles. DivIO\_Q2 to Q5 are dummy variables for quintiles 2–5 of the DivIO portfolios. From quintile 1 to 4, the innovation measures are monotonically increasing. From quintile 4 to 5, the innovation level decreased a little but remains similar. This observation is consistent with the notion that DivIO has an effect up to a level. After certain threshold, the effect is not significant and may reverse a little bit. The reverse can be due to other factors such as the potential negative effect of distraction.

VARIABLES	(1) NumPat <sub>t+2</sub>	(2) PatValue <sub>t+2</sub>	(3) Citation <sub>t+2</sub>
DivIO_Q2	6.3819*** (8.791)	199.7953*** (2.947)	13.3603*** (7.658)
DivIO_Q3	8.5471*** (16.162)	283.7637*** (13.223)	17.3806*** (15.668)
DivIO_Q4	10.6338*** (24.840)	311.8402*** (20.825)	22.7121*** (22.826)
DivIO_Q5	8.4795*** (24.756)	296.9141*** (20.653)	17.7416*** (22.855)
IO Quintiles	YES	YES	YES
Observations	134,441	134,441	134,441
R-squared	0.005	0.004	0.005

t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## Appendix 3:

### Quality of the matched sample

Appendix 3 provides summary statistics of the matching variables for the matched samples. *IO* is the fraction of outstanding stocks owned by the institutional investors. *ROA* is return of assets. *Leverage* is liability over total asset. *Cash* is the firm's cash over total asset. *Q* stands for the firm's Tobin's Q. *KZ-index* is the Kaplan-Zingales measure of financial constraints. *Tangibility* is property, plant, and equipment over total assets. *Hindex* is the Herfindahl index of the firm's industry. *C-index* is a common ownership measure following Lewellen and Lowry (2021). *InvSize* is the average AUM (millions) of the institutional investors holding the firm. *InvRet* is the average year-to-year return for the firm's institutional investors. This table shows that there are statistically significant differences between the treated firms and control firms.

VARIABLES	Mean (Treated)	Mean (Control)	Diff	Std (Treated)	Std (Control)	Correlation	Covariance
IO	51.03%	46.02%	5.01%***	0.2586	0.2441	0.8684***	0.0548
ROA	9.65%	9.02%	0.63%***	0.2182	0.1803	0.7326***	0.0288
Leverage	23.39%	22.88%	0.51%***	0.2538	0.2151	0.7480***	0.0408
Cash	15.62%	14.92%	0.60%***	0.1969	0.1940	0.8730***	0.0334
Q	1.9984	1.7606	0.2366***	2.1163	1.8362	0.8312***	3.2367
KZ-Index	0.5095	0.5950	-0.0828***	2.2123	1.9617	0.6584***	2.8187
Sales (millions)	1,717.81	890.35	827.46***	5,884.23	2,615.95	0.6539***	1.0061e <sup>+07</sup>
Tangibility	0.3019	0.2941	0.0077***	0.2472	0.2415	0.9031***	0.0539
Hindex	0.2333	0.2252	0.0081***	0.1796	0.1669	0.8728***	0.0261
C-index*1000	27.31	29.12	1.82**	41.44	43.85	0.7123***	1,294.35
InvSize (millions)	36.21	27.31	8.91***	41.97	32.93	0.7979***	1,102.76
InvRet	5.17%	3.89%	1.28%	0.1293	0.1087	0.7299***	0.0103

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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