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Do Mergers and Acquisitions Activities of Large-Cap Companies Affect Private Equity Firms' Investment Strategies?

By

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Abstract

Almost all mergers and acquisitions deals were done by private equity firms and strategic investors, which are incumbent companies that purchase another company to achieve synergies. Private equity firms and strategic investors can be competitors when they are bidding on the same target company, but strategic investors can also become potential buyers of private equity fund's portfolio companies. Given their unique relationship, I selected the largest 20 strategic investors from 10 sectors and used logistic regression and panel data analysis to answer the question: Do mergers and acquisitions (M&A) activities of large-cap corporations in the previous year affect private equity firms' investment decisions on similar companies? The logistic regression showed that if the target company has the same SIC code as the companies acquired by big-cap corporations in the previous year, this deal has 65.7% lower odds to be PE funded. The panel data analysis tells us for every 1% increase in the percentage of companies acquired by big-cap companies in a particular sector in the previous year, PE firms would acquire 0.159% more companies in that sector. These results jointly showed that if the big-cap companies made more acquisitions in a particular sector in the previous year, in the current year, private equity firms would acquire fewer similar companies (companies with the same SIC code), but would increase their investments in other companies of that sector. This finding can help investors, business owners, and stock traders make or adjust their investment decisions.

1. Introduction

Private equity (PE) firms are crucial players in the investment world. They have grown substantially since the 1980s and are currently managing over $6 trillion in the United States alone (Morran and Petty 2022). Although the number of PE deals decreased at the beginning of the pandemic due to a lack of available finance, the inability to travel, conduct due diligence, and negotiate face-to-face (Saenz 2020), PE firms have already picked up speed to invest. In the first half of 2022, there were 10,250 private equity deals worldwide with a total of $349.5 billion in transaction value, which represent 71% of global investment (Burnett 2022).

Private equity firms, also known as financial sponsors, serve as the general partners to pool funds from limited partners, utilize a small portion of their cash and a lot of debt financing to acquire companies with the potential for substantial growth, get involved in the operation to add values with managing partners' expertise, and exit after six years on average (Joenväärä, Mäkiaho and Torstilaeither 2022) by selling to other investors or an IPO.

Typically, private equity firms use the leveraged buyout (LBO) as their primary investment strategy. In an LBO acquisition, PE firms pay a portion of acquiring price with their cash raised from limited partners and pay the rest with debts borrowed from banks or other financial institutions. Then, PE firms use the cash flow generated by the target business to pay down the debt, and exit when the opportunity comes. There are generally three ways to make money in an LBO deal (Sam Shiah 2020):

I. As the PE firms pay down the debt with cash flow from the acquired company, their equity ownership increases;

II. As the PE firms improved the performance of the target or achieved synergies with their portfolio companies, the target can be sold at a higher multiple;

III. The market conditions improve, so the target companies' valuation increase even if PE firms are not able to add value.

Therefore, it is crucial to select a target company that not only has the potential to be sold at a higher multiple or go public through an IPO but also can generate consistent cash flows. On the other hand, strategic buyers or strategic investors, incumbent companies that purchase another company to achieve synergies, also play an important role in mergers and acquisitions deals and they frequently look for suitable targets to expand their own business both vertically and horizontally. Among all companies in the United States, the biggest strategic buyers are usually companies with the largest market capitalization that we are familiar with such as Apple, Microsoft, Amazon, etc. PE firms and strategic investors could be competitors when they pursue the same target company, but strategic investors can also become potential buyers of PE firms' portfolio companies.

As the primary funders of private equity firms, limited partners, usually pension funds, family offices, high-net-worth individuals, and insurance companies, would like to gather information on as many private equity funds as possible before deciding which funds they should invest in. However, private equity transactions are non-transparent, and it is nearly impossible for outside investors to find useful information on PE funds unless limited partners contact each fund individually and show strong interest (Snow 2007). Nevertheless, almost all the biggest strategic buyers are publicly traded companies that are required to file important information to SEC. With this unique relationship between private equity funds and strategic investors, can we learn more about private equity funds with information on the investment activities of strategic buyers? I don't think we can know about any deal-specific information, but it is possible to have a big picture of where the money of private equity funds is going. In this paper, I will use

statistical models to find out: Do mergers and acquisitions (M&A) activities of large-cap corporations in the previous year affect private equity firms' investment decisions on similar companies?

My hypothesis is that mergers and acquisitions activities of large-cap companies can affect private equity firms' investment decisions. After witnessing the M&A activities of large-cap corporations, private equity funds might either increase their investments in similar companies as the ones being bought by big-cap companies or decrease their investments. Since this is the first attempt trying to answer this question, I am not sure which direction the effect will go, but there seem to be valid reasonings for both directions:

I. Positive effect:

Although IPO is a preferable exit strategy for private equity funds, selling to other investors is the most common exit option because IPO requires a lot of extra labor and approval (La Lande 2011). The big-cap companies are dominant players in their own sectors. Their investment decisions may jointly represent the market trends. Since almost all PE firms seek exit opportunities and big-cap companies could be a great choice of potential buyers, PE firms would acquire more similar companies so that there is a greater possibility to exit.

II. Negative effect:

Most of the time, big-cap companies have a much larger cash reserve and easier access to debt so they pay a higher multiple in general when the target is attractive (Axelson et al. 2013). Additionally, as strategic buyers, big-cap companies can achieve synergies after acquisition. This is an important factor that distinguishes private equity funds from strategic buyers. These potential synergies can help strategic buyers cut expenses and boost sales, which motivate them to pay more to acquire desired targets. On the other hand, PE funds tend to pay lower multiple to

acquire companies that are overlooked by strategic buyers, and then add value through operations. Therefore, PE funds might acquire fewer similar companies and spend more time finding undervalued companies instead.

Private equity deals are risky and have a failure rate of 27% on average (Toll 2017), thus limited partners do not invest all of their money into private equity. Their diversified investment portfolios consist of stocks, fixed income, private equity, real estate, hedge funds, etc. It is important, especially for the interests of limited partners, to answer my research question because, with the results, we can know how private equity firms will allocate their funds after witnessing the M&A activities of big-cap companies in the previous period. If limited partners can have a big picture of what companies private equity firms are more likely to invest in advance, they can adjust their investment portfolios accordingly before making any official commitments. This information will also be useful for business owners that plan to sell their companies as they can have a rough idea on the prospect of selling. Last but not the least, this information help stock traders detect market singles since the increase or decrease of funding in a particular sector might affect stock prices.

2. Literature Review

The previous works of literature primarily focused on the value creation of PE firms and their ability to identify high-growth targets. A group of scholars found that the return of private equity firms follows a J-Curve because private equity firms typically have negative returns and cash flows in the early stage of investment and achieve positive returns later on (Diller, Herger, Wulff, and Dynamics 2009). It's also shown that the expertise brought by private equity firms can lead to better performance in the operation of portfolio companies (Acharya, Gottschalg, Hahn, and Kehoe 2013). Additionally, PE firms are capable of identifying opportunities that

were overlooked by strategic investors (Dittmar, Li, and Nain 2012). In terms of PE firms' investment criteria, one research showed that revenue growth is the most important metric followed by the capability to add values, management team, and profitability (Block, Fisch, Vismara, and Andres 2019). However, the question of whether or not the PE firm would adjust its investment strategy based on what target companies big-cap corporations acquired was still unanswered.

In 2020, Kamepalli, Rajan, and Zingales proposed the idea of a "Kill Zone" for Venture Capital backed startup companies in the platform business. Their study showed that there is a significant decrease in VC funding and the number of VC-funded deals for startup companies in the platform business after large incumbent platforms acquire new entrants due to a reduction in prospective payoffs (Kamepalli, Rajan, and Zingales 2020). Although limited to platform businesses, this paper inspired my idea that there might be a similar phenomenon for private equity funds across different sectors.

3. Data and Data Preparation

The data I used for this thesis paper was the SDC – Mergers and Acquisitions dataset collected by Thomson Reuters and Refinitiv from 2000 to 2022. This dataset is continually updated and I downloaded it from the Wharton Research Data Services (WRDS) website on September 12th, 2022. Originally, this dataset consists of 211,776 rows and 146 columns (population). Below is a table describing important variables in my study. I will then describe the analytic sample used for my research.

Table 1: Key Variable Names and Descriptions

Variable Names	Descriptions
Date Announced	When was the deal announced
Target Name	Names of target companies
Acquirer Name	Names of acquiring companies
Acquirer Nation	Where were the acquirers located
Target Nation	Where were targets located
Target Public Status	Was the target public or private
Acquirer Public Status	Was the acquirer public or private
Deal is a Repurchase Flag	The deal was a repurchase or not
Enterprise Value ($mil)	The enterprise value of targets
Percentage of Shares Acquired	How many percent of shares were acquired
TR Acquirer Macro Description	Primary sectors acquirers belonged to
TR Target Macro Description	Primary sectors targets belonged to
Target Primary SIC Code	SIC codes of target companies
Acquirer Ultimate Parent Name	Names of acquirers' ultimate parent companies
Acquirer is a Private Equity Firm (Yes/No Flag)	Was the acquirer a private equity firm or not
Date Effective	When did the deal become effective
Form of Transaction	Was the deal a merger, acquisition, or an exchange offer
Recapitalization Flag	Was the deal a recapitalization or not
Ranking Value incl Net Debt of Target (USD Mil)	The total amount paid to targets including net debts
Transaction is a Spinoff Flag	Was the deal a Spin-off transaction or not
Transaction is a Splitoff Flag	Was the deal a Split-off transaction or not
Deal Status	Was the deal completed, rumored, pending, or withdrawn
Acquirer Market Value 4 Weeks Prior to Announcement ($mil)	Market values of acquiring companies 4 weeks prior to deal announcement
Target Market Value 4 Weeks Prior to Announcement ($mil)	Market values of target companies 4 weeks prior to deal announcement
Target Net Income LTM ($mil)	Net income of targets in last 12 months ($mil)
Target Net Assets ($mil)	Net assets of target companies ($mil)

For this paper, I filtered and cleaned the original dataset based on what information is

relevant to my area of concern. First of all, I focused my study on deals that happened in the United States from 2002 through 2021, including data lagged one year. I used the effective date instead of the announcement date because the effective date is when the agreement between two legal entities becomes binding. Another important factor I considered was to remove all the deals that could be classified as a repurchase, a recapitalization, an exchange offers, a buyback, a spin-off, or a split-off. The logic behind this adjustment was that I only want to analyze deals that involve two independent parties that enter an agreement to merge, acquire, or be acquired. The removed types of deals (repurchase, recapitalization, exchange offer, buyback, spinoff, and split off) are what corporations do internally to achieve their financial objectives. Additionally, I only selected deals that were completed with at least 50% of shares being acquired because I do not want withdrawn or rumored deals and minor stake acquisitions to bias my results. The final cleaned sample dataset has 22,536 deals.

Big-cap companies play an important role in my study; therefore, it is also necessary to identify these companies across major business sectors. I followed the Global Industry Classification Standard (GICS) to divide all companies into 11 sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer, Staples, Healthcare, Financials, Information Technology, Communication Services, Utilities, and Real Estate. I checked these sectors against the TR Target Macro Description column of my dataset and most of them align. To obtain information on their size, I used data from pitchbook.com where I selected U.S. public companies trading either on NASDAQ or New York Stock Exchange, then ranked these companies based on their enterprise value. I ranked them based on enterprise values because target companies' debts and cash need to be considered during an M&A, and equity values (price per share * shares outstanding) cannot show a full picture of the deal. The only adjustment I

made here was to combine energy and utilities to be one sector since there are a lot of overlaps. Thus, I have 10 sectors and focus on the top 20 companies within each. Below is a table listing the 20 largest companies I selected for each sector:

Table 2: Sectors and Big-Cap Companies

Energy & Utilities	Materials and Resources	Industrials	Consumer Discretionary	Consumer Staples
ExxonMobil	The Sherwin-Williams	Berkshire Hathaway	The Home Depot	Walmart
Chevron	Air Products and Chemicals	Tesla	The Walt Disney Company	Procter & Gamble
NextEra Energy	Ecolab	United Parcel Service	Nike	Coca-Cola
ConocoPhillips	Freeport-McMoRan	Raytheon Technologies	Lowe's Companies	Pepsico
Energy Transfer	Dow	Union Pacific	The Estee Lauder Companies	Costco Wholesale
Duke Energy	Newmont	Deere	3M	Starbucks
Southern Company	International Flavors & Fragrances	Ford	Netflix	Mondelez International
Dominion Energy	LyondellBasell Industries Holdings	General Motors	Booking Holdings	Altria Group
American Electric Power Company	Dupont de Nemours	Honeywell	Marriott	Colgate-Palmolive
Xcel Energy	PPG	Boeing	Uber	Kraft Heinz
Occidental Petroleum	Corning	Caterpillar	Target	McDonald's
Enterprise Products Partners	Nucor	S&P Global	Best Buy	Philip Morris International
Consolidated Edison	Ball	Lockheed Martin	Garmin	Keurig Dr Pepper
Edison International	Albemarle	Stanley Black & Decker	Hasbro	Constellation Brands
Exelon	Avantor	FedEx	Newell Brands	General Mills
Entergy	Amcor	General Electric	Whirlpool	Archer Daniels Midland
Kinder Morgan	Vulcan Materials Company	CSX (Jacksonville)	Fortune Brands Home & Security	Kimberly-Clark
Eversource Energy	International Paper	General Dynamics	Williams-Sonoma	Sysco
Marathon Petroleum	The Mosaic	Norfolk Southern	Hubbell	Hershey
Republic Services	The Clorox Company	Illinois Tool Works	Arrow Electronics	Monster Beverage

Healthcare	Financial Services	Information Technology	Communication and Networking	Real Estate Services
UnitedHealth Group	Visa	Apple	Verizon Communications	Digital Realty
AbbVie	JPMorgan	Microsoft	AT&T	Invitation Homes
Eli Lilly	Mastercard	Alphabet	T-Mobile USA	Lennar
Pfizer	Bank of America	Amazon.com	Comcast	Simon Property Group
Merck & Co.	Wells Fargo	Nvidia	Qualcomm	UDR
Thermo Fisher Scientific	Morgan Stanley	Meta Platforms	Cisco Systems	Camden Property Trust
Danaher	Goldman Sachs	Oracle	Charter Communications	Brixmor Property Group
Abbott	Citigroup	Broadcom	American Tower	Toll Brothers
Bristol-Myers Squibb	Capital One Financial	Adobe Systems	Crown Castle International	Hilton Grand Vacations
CVS Health	PNC	Salesforce.com	L3 Harris Technologies	Howard Hughes
Amgen	Lincoln Financial Group	IBM	SBA Communications	Zillow Group
Medtronic	Cigna	Intel	Amphenol	Keller Williams Realty Inc
Gilead Sciences	Chubb	Texas Instruments	TE Connectivity	Sothebys Holdings Inc
HCA Management Services	Equitable Holdings	Intuit	Motorola Solutions	Opendoor Technologies
Stryker	Marsh & McLennan Companies	Advanced Micro Devices (AMD)	Altice USA	Jbg Smith Properties
Becton, Dickinson and Company	CME Group	Applied Materials	Liberty Global (UK)	Broadstone Net Lease
Zoetis	Truist	Analog Devices	Liberty Broadband	Urban Edge Properties
Walgreens Boots Alliance	Ally Financial	ServiceNow	Ubiquiti	Meritage Homes
Intuitive Surgical	Fifth Third Bank	Fiserv	CommScope	Armada Hoffler Properties
Humana	Progressive Corporation	Fidelity Natl Info Svcs Inc	Telephone & Data Systems	Prologis

4. Methodology and Results

To answer my research question, I employ two methods for analysis, which are logistic regression, and panel data analysis. I initially attempted to do an event student analysis with targets' primary Standard Industrial Classification Codes (SIC Codes), which tell us what specific industry this company belongs to. Two target companies are similar if they have the same SIC code. I would first pick a base year t and one of the ten sectors, then check what target

companies the big-cap firms in that sector acquire and what primary SIC codes are for their targets in that sector. For years t-1 and t+1, I calculated: out of all the deals that have private equity firms as the acquirer in that sector, how many targets are similar to the ones being acquired by big-cap companies in year t and what is the proportion of the total number of PE acquired deals? With the two proportions in year t-1 and year t+1, I could run two proportion z-tests to check whether or not there is a significant difference. However, this study design ended up with an extremely small sample size that cannot be used. In a summary, the logistic regression showed a negative effect, whereas the panel data analysis showed a positive effect, and both results are significant. I will explain the results in detail in the next section.

4.1 Logistic Regression

In this section, I will talk about the analysis using logistic regression and share its result. Logistic regression can be used to model the probability of an event happening. In this model, I want to get results that can help me learn how private equity firms adjust their investment strategies on target companies after knowing what big-cap companies did in the previous period. For my study, the dependent variable is whether or not the acquirer is a private equity fund. The independent variables are:

Table 3: Independent Variables for Logistic Regression

Dummy Variables	Description
Target in Same Big SIC Dummy	Whether or not there is an acquisition done by large-cap companies in the same SIC Code in the previous year
Acquirer Market Value 4 Weeks Prior to Announcement ($mil)	Market values of acquiring companies 4 weeks prior to deal announcement
Target Market Value 4 Weeks Prior to Announcement ($mil)	Market values of target companies 4 weeks prior to deal announcement
Target Net Income LTM ($mil)	Net income of targets in last 12 months ($mil)
Target Net Assets ($mil)	Net assets of target companies ($mil)

For my research, the coefficient and significance of 'Target in Same Big SIC Dummy' is what I care about the most. It measures whether or not there is an acquisition done by large-cap companies in the same SIC Code in the previous year. I lagged by one year because it takes time for PE firms to react and it doesn't make sense for them to witness a deal completed by large-cap companies and then wait more than one year to take any actions. To help illustrate: if a deal happened in 2019 and the target primary SIC code was 0218, and in 2018 the top 200 big-cap companies acquired companies with SIC Codes (1211, 0124, 3489, 2399, 1293) and let's call this set A. Then the binary variable 'Target in Same Big SIC Dummy' = 0 in this case and = 1 otherwise, because 0218 does not belong to set A. The coefficient of this binary variable can tell us how would knowing the target has the same SIC code as companies acquired by big-cap investors in the previous year affect the probability of the acquirer is a private equity firm.

The original dataset includes many deal-specific variables such as rank values, debt offer dummy, deal status, etc., but I did not use them because they are not helpful to answer my research question. In this logistic regression model, all my independent variables measure

company-specific metrics such as size, assets, and profitability. In the dataset, many variables are measuring the same metrics, so I only chose one representative variable for each important metric to avoid multicollinearity. I chose "Acquirer Market Value 4 Weeks Prior to Announcement ($mil)" to measure the size of acquiring firm, "Target Market Value 4 Weeks Prior to Announcement ($mil)" to measure the size of the target company, "Target Net Income LTM ($mil)" to measure target's profitability, and "Target Net Assets ($mil)" to measure target assets vs. liabilities. These variables have a lot of missing values that I have to remove. The issue here is that many of the deals were conducted by private companies and these data were hard to find most of the time. Sometimes, the two parties of the transaction may even choose not to disclose any information. This issue also bothers major investment banks on Wall Street when analyzing private transactions. After I removed all the missing values, I only had 1,519 rows of data compared to 22,536 rows, but 1,519 observations are still enough to run the logistic regression and produce a reliable result.

Equation 1: Logistic Regression Full Model

$$\text{logit(p)} = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \text{SIC} + \beta_2 \text{AMV} + \beta_3 \text{TMV} + \beta_4 \text{TNI} + \beta_5 \text{TNA}$$

Equation 1 shows the full logistic regression model, where β_0, β_1, β_2, β_3, β_4, and β_5 are the intercept and coefficients. SIC represents the Target in Same Big SIC Dummy, AMV represents the acquirer market value, TMV represents the target market value, TNI represents the target net income, and TNA represents the target net asset. First, I ran the full model and then ran the model again with only Target in Same Big SIC Dummy as my independent variable to show how including control variables would change the coefficient β_1. Below are the results:

Figure 1: Logistic Regression Full Model Results

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8818  -0.4451  -0.0505   0.0000   7.0427

Coefficients:
                                                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                                                     -7.160e-01  1.512e-01  -4.736 2.18e-06 ***
`Target in Same Big SIC Dummy`                                  -1.071e+00  2.156e-01  -4.969 6.71e-07 ***
`Acquiror Market Value 4 Weeks Prior to Announcement ($mil)` -1.684e+00  2.635e-01  -6.392 1.64e-10 ***
`Target Market Value 4 Weeks Prior to Announcement ($mil)`   -4.432e-06  2.193e-05  -0.202  0.83979
`Target Net Income LTM ($mil)`                                 7.222e-04  2.589e-04   2.790  0.00528 **
`Target Net Assets ($mil)`                                     7.321e-05  8.249e-05   0.888  0.37480
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 829.60  on 1518  degrees of freedom
Residual deviance: 588.37  on 1513  degrees of freedom
AIC: 600.37

Number of Fisher Scoring iterations: 18
```

Figure 2: Logistic Regression Model Without Control Variables Results

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5073  -0.5073  -0.3422  -0.3422   2.3945

Coefficients:
                                Estimate Std. Error z value Pr(>|z|)
(Intercept)                     -1.98549    0.02793  -71.09   <2e-16 ***
`Target in Same Big SIC Dummy` -0.82270    0.05062  -16.25   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 13750  on 22535  degrees of freedom
Residual deviance: 13464  on 22534  degrees of freedom
AIC: 13468

Number of Fisher Scoring iterations: 5
```

In the full model, Intercept, Target in Same Big SIC Dummy, Acquirer Market Value 4 Weeks Prior to Announcement ($mil), and Target Net Income LTM ($mil) have p-values very close to zero, which means they are significant at the 95% confidence level. Target Market Value 4 Weeks Prior to Announcement ($mil) and Target Net Assets ($mil) are not significant in

predicting whether the acquiring firm is a private equity fund. The table below shows the interpretation of the coefficients:

Table 4: Interpretations of Logistic Regression Coefficients

Coefficients	Interpretations
$\beta_0 = -0.716$	The log odds value for deals that both the target and acquirer have a market value of zero, and the target has no net income and net asset. Also, the targets do not have matching SIC codes.
$\beta_1 = -1.071$	Holding all other variables at a fixed value, the odds of being a PE-acquired deal if the target has a matching SIC code (SIC = 1) over the odds of being a PE acquired deal if the target does not have a matching SIC code (SIC = 0) is $e^{-1.071} \approx 0.343$. In terms of percent change, we can say that the odds for deals with a target having a matching SIC code are (1 – 0.343) = 65.7% lower than the odds for deals without a target having a matching SIC code.
$\beta_2 = -1.684$	Holding all other variables at a fixed value, for every $1 million increase in acquirer market value, the log-odds of being a PE-acquired deal decrease by 1.684.
$\beta_3 = -4.432 \times 10^{-6}$	Holding all other variables at a fixed value, for every $1 million increase in target market value, the log-odds of being a PE-acquired deal decrease by 4.432×10^{-6}.
$\beta_4 = 7.222 \times 10^{-4}$	Holding all other variables at a fixed value, for every $1 million increase in target net income, the log-odds of being a PE-acquired deal increase by 7.222×10^{-4}.
$\beta_5 = 7.321 \times 10^{-5}$	Holding all other variables at a fixed value, for every $1 million increase in target net asset, the log-odds of being a PE-acquired deal increase by 7.321×10^{-5}.

The model with no control variables also gave us a similar coefficient as the full model and the result was also significant. To pick the better model, I compared the Akaike Information Criterion and chose the full model since its AIC = 600.37, which is smaller than the single

variable model's AIC = 13468. I also calculated the Pseudo R-Squared, which measures the overall effect size for both models and the p-values associated with each Pseudo R-Squared using Chi-Squared Distribution to prove this R-Squared is significant. Table 5 summarizes the result.

Table 5: Pseudo R-Squared and P-Values

	Full Model	**Single Variable Model**
Pseudo R-Squared	0.2908	0.0208
P-Value	< 0.0005	< 0.0005

The Pseudo R-Squared for the full model is much higher than the Pseudo R-Squared for the single variable model because having only a binary variable as the independent variable will lower the Pseudo R-Squared as there won't be much covariance. Both Pseudo R-Squareds are significant. To answer my research question, the logistic regression showed that if the target company is similar to the companies acquired by big-cap corporations in the previous year, this deal has 65.7% lower odds to be PE funded.

4.2 Panel Data Analysis

The second method I used is the Panel Data Analysis. In this analysis, I no longer focus on the SIC code of targets. Instead, I used my original dataset to create a panel dataset goes from 2002 to 2021 (20 years) for each sector. From this analysis, I want to learn how the M&A activities of big-cap companies would impact private equity firms' investment strategies on the sector level. The entire panel dataset consists of four columns: Sector, Year, PE Proportion, and Previous Big-Cap Proportion.

Table 6: Panel Dataset Variables and Descriptions

Variables	Descriptions
Sector	10 sectors I used for the previous analysis
Year	From 2002 to 2021 because 2022 is not over yet
PE Proportion ($P_{i,t}$)	In a particular year t and sector i, how many percent of the targets were acquired by a private equity company
Previous Big-Cap Proportion ($B_{i,t-1}$)	In a particular sector i and year t-1, what percent of companies were acquired by big-cap companies (the lagged value $B_{i,t-1}$)

4.2.1 Pooled OLS

In this section, I will discuss the Pooled OLS performed on this panel data and share the result. For the pooled OLS, the equation is:

Equation 2: Pooled OLS

$$P_{i,t} = \beta B_{i,t-1} + e_{i,t}$$

I have explained the variables in the table above, and $e_{i,t}$ is the error term. For my study, β is what I care about. If beta is negative, it means after witnessing the big-cap companies' M&A activities in year t-1, the PE firms actually acquire fewer companies in the same sector in year t. If beta is positive, it means after witnessing the big-cap companies' M&A activities in year t-1, the PE firms actually acquire more companies in the same sector in year t. To be consistent with the logistic regression, I also used lagged one year. In table Appendix A, I shared a demo of my panel dataset. Here is the result of this pooled OLS regression:

Figure 3: Results for Pooled OLS

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.13879 -0.06412 -0.01214  0.05049  0.29472

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.104263   0.007564  13.785   <2e-16 ***
Previous_BigCap_Proportion 0.069051   0.081848   0.844      0.4
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07989 on 198 degrees of freedom
Multiple R-squared:  0.003582,  Adjusted R-squared:  -0.001451
F-statistic: 0.7117 on 1 and 198 DF,  p-value: 0.3999
```

The coefficient for the Previous Big-Cap Proportion is positive, but the p-value is greater than 0.05. Therefore, this result is not significant at the 95% confidence level. To interpret the coefficient that I care about: for every 1% increase in the percentage of companies acquired by big-cap companies in a particular sector i and year t-1, PE firms would acquire 0.069% more companies in that sector in the next year. Since this coefficient is not significant, there must be something else I need to consider.

The problem here is that pooled OLS assumes that the coefficients are consistent for all sectors, the covariance between the independent variables and the error term is zero, and the error term is independently and identically distributed in $(0, \sigma_e^2)$. However, these assumptions are almost guaranteed to be violated in this case. First of all, it is impossible that the 10 sectors all have the same characteristics. For example, the consumer staples sector is very different from the information technology sector in so many different ways such as business models, revenue models, products, and marketing strategies, etc. It's very likely that Previous Big-Cap Proportion ($B_{i,t-1}$) is significantly associated with some omitted variables. In addition to its own effect, it is

also reflecting the effects of omitted variables. That's why it's currently not significant. Then, I tried the fixed-effect and random-effect models to solve this problem.

4.2.2 Fixed-Effect and Random-Effect Models

I first ran the model with sector fixed-effect. Here are the equation and results:

Equation 3: Sector Fixed-Effect Regression

$$P_{i,t} = \beta_0 + \beta_1 S_1 + \beta_2 S_2 + \beta_3 S_3 + \beta_4 S_4 + \beta_5 S_5 + \beta_6 S_6 + \beta_7 S_7 + \beta_8 S_8 + \beta_9 S_9 + \gamma B_{i,t-1} + e_{i,t}$$

Figure 4: Results for Sector Fixed-Effect Regression

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.183005 -0.037893 -0.008752  0.033962  0.312281

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.167175   0.013996  11.945  < 2e-16 ***
Previous_BigCap_Proportion 0.263299   0.082564   3.189  0.00167 **
SectorCS                  -0.047408   0.019757  -2.400  0.01739 *
SectorEnergy and Power    -0.105253   0.020341  -5.174 5.81e-07 ***
SectorFinancials          -0.139726   0.019945  -7.006 4.20e-11 ***
SectorHealthcare          -0.096348   0.020978  -4.593 7.97e-06 ***
SectorIndustrials         -0.010662   0.019856  -0.537  0.59193
SectorIT                  -0.108730   0.021327  -5.098 8.29e-07 ***
SectorMaterials            0.004472   0.020370   0.220  0.82645
SectorReal Estate         -0.129002   0.019786  -6.520 6.24e-10 ***
SectorTelecommunications  -0.115819   0.022759  -5.089 8.65e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06246 on 189 degrees of freedom
Multiple R-squared:  0.4187,    Adjusted R-squared:  0.3879
F-statistic: 13.61 on 10 and 189 DF,  p-value: < 2.2e-16
```

In the equation, S stands for sectors. In this model, the base sector is consumer discretionary. SectorCS stands for the consumer staples sector. The coefficients are significant at the 95% level for all sectors except Materials and Industrials. The coefficient for Previous Big-Cap Proportion is positive and significant. This coefficient also increased in magnitude and p-

value becomes 0.00167. To interpret the coefficient that I care about: for every 1% increase in the percentage of companies acquired by big-cap companies in a particular sector i and year t-1, PE firms would acquire 0.263% more companies in that sector in the next year. The reported R-Square is now 0.3879. When I added the sector dummy variables into the model, Previous Big-Cap Proportion becomes significant because it doesn't capture the effects of the omitted variables anymore and the coefficient only reflects its true effect.

Also, it is possible that private equity firms made more acquisitions over the years regardless of what big-cap companies did. To ensure the coefficient captures the true effect, I ran the fixed-effect model with sector and years. The results are captured in figure 5. The coefficient of Previous Big-Cap Proportion is unsurprisingly lower but still significant. It means that for every 1% increase in the percentage of companies acquired by big-cap companies in a particular sector i and year t-1, PE firms would acquire 0.159% more companies in that sector in the next year. With 2002 as the base year, the coefficients for 2003 to 2021 are all positive and they are all significant except for 2003 and 2009. This information tells us that in the past 20 years, private equity funds were acquiring more and more companies. In the 2022 private markets report, McKinsey also noted similar findings. From 2003 to 2008, private equity funding increased every year. The funding dropped significantly in 2009, but continued to grow soon afterward and became quadrupled in 2021 (McKinsey 2022).

Figure 5: Results for Sector and Year Fixed-Effect Regression

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.127888 -0.021771 -0.000026  0.023064  0.263486

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.090190   0.020450   4.410 1.83e-05 ***
Previous_BigCap_Proportion 0.158657   0.078188   2.029 0.044001 *
SectorCS                  -0.047952   0.016911  -2.836 0.005131 **
SectorEnergy and Power    -0.099094   0.017522  -5.656 6.45e-08 ***
SectorFinancials          -0.136222   0.017108  -7.963 2.30e-13 ***
SectorHealthcare          -0.087392   0.018183  -4.806 3.36e-06 ***
SectorIndustrials         -0.008098   0.017015  -0.476 0.634718
SectorIT                  -0.098535   0.018543  -5.314 3.33e-07 ***
SectorMaterials            0.010783   0.017552   0.614 0.539802
SectorReal Estate         -0.127544   0.016941  -7.529 2.87e-12 ***
SectorTelecommunications  -0.101490   0.020011  -5.072 1.02e-06 ***
YearDum2003                0.036900   0.023910   1.543 0.124618
YearDum2004                0.054511   0.023912   2.280 0.023872 *
YearDum2005                0.057832   0.023944   2.415 0.016781 *
YearDum2006                0.061751   0.024000   2.573 0.010938 *
YearDum2007                0.089530   0.024039   3.724 0.000266 ***
YearDum2008                0.063760   0.023968   2.660 0.008556 **
YearDum2009                0.035287   0.024166   1.460 0.146083
YearDum2010                0.074295   0.024150   3.076 0.002443 **
YearDum2011                0.084946   0.024152   3.517 0.000560 ***
YearDum2012                0.085596   0.024056   3.558 0.000484 ***
YearDum2013                0.065731   0.024388   2.695 0.007742 **
YearDum2014                0.060931   0.024037   2.535 0.012152 *
YearDum2015                0.052619   0.024562   2.142 0.033597 *
YearDum2016                0.108389   0.024847   4.362 2.23e-05 ***
YearDum2017                0.130103   0.024108   5.397 2.25e-07 ***
YearDum2018                0.110342   0.024114   4.576 9.11e-06 ***
YearDum2019                0.146887   0.024044   6.109 6.63e-09 ***
YearDum2020                0.111554   0.024470   4.559 9.80e-06 ***
YearDum2021                0.131466   0.023950   5.489 1.45e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05346 on 170 degrees of freedom
Multiple R-squared:  0.6169,    Adjusted R-squared:  0.5516
F-statistic:  9.44 on 29 and 170 DF,  p-value: < 2.2e-16
```

Then, I ran the random-effect model in R. Here is the result:

Figure 6: Results for Random-Effect Regression

```
Effects:
                   var  std.dev share
idiosyncratic 0.003902 0.062462 0.586
individual    0.002757 0.052512 0.414
theta: 0.743

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.185874 -0.038461 -0.012597  0.036046  0.299178

Coefficients:
                           Estimate Std. Error z-value Pr(>|z|)
(Intercept)                0.093585   0.017907  5.2262 1.73e-07 ***
Previous_BigCap_Proportion 0.242832   0.080902  3.0015 0.002686 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.80953
Residual Sum of Squares: 0.7743
R-Squared:      0.043521
Adj. R-Squared: 0.03869
Chisq: 9.00928 on 1 DF, p-value: 0.0026861
```

The coefficient for Previous Big-Cap Proportion is still positive and significant. I ran the Hausman Test to choose between both the fixed-effect models and the random-effect model. The null hypothesis for the Hausman test is that the preferred model is the random-effect model. We can safely reject the null hypothesis since p-values are nearly zero and we can conclude that the fixed-effect model is more appropriate. Since the pooled OLS gave us a negative R-Squared and an insignificant result, the results from the fixed-effect model will be used in the conclusion section.

5. Conclusion

In the previous sections, I showed the logistic regression produced a significant result: if the target company has the same SIC code as the companies acquired by big-cap corporations in

the previous year, this deal has 65.7% lower odds to be PE funded. A possible explanation might be that PE firms are reluctant to compete with big-cap strategic investors for deals. Wall Street veteran, Jack Bloom, commented on this: “Strategic investors pay higher multiple because they can achieve synergies and typically, PE firms only get the deal when strategic investors don’t want it” (Bloom 2022). Also, it might be because acquisition done by big-cap companies implies that selling to a third party is more likely than IPO as an exit strategy, which means a lower potential ROI for PE funds.

On the other hand, the panel data analysis with the fixed-effect model tells us that for every 1% increase in the percentage of companies acquired by big-cap companies in a particular sector in the previous year, PE firms would acquire 0.159% more companies in that sector. A possible explanation for this positive effect might be that PE firms intend to acquire more companies in the sector that big-cap companies focused on so that their portfolio companies have a better possibility to be acquired as an exit strategy, especially when IPOs are difficult.

The coefficients I got from the logistic model and the panel data analysis have opposite signs. The results seem to be contradictory, but in fact, they are not. The logistic regression model was on SIC codes of target companies, whereas the panel data analysis is on the sector level, which is much broader. For example, the real estate sector alone covers more than 20 SIC codes. So, together, the logistic regression and panel data analysis tell us that if the big-cap companies made more acquisitions in a particular sector in the previous year, in the current year, private equity firms would acquire fewer similar companies (companies with the same SIC code), but would increase their investments in other companies of that sector.

This result can help investors, business owners, and stock traders make their investment decisions. From the investors’ perspective, with information on what companies big-cap

corporations acquired last year, they can have a big picture of how private equity firms would allocate their money this year. PE funds would invest in fewer similar companies as the ones acquired by big-cap companies last year but would invest more in other companies that were not looked at by big-cap investors in that same sector. If investors found their interests align with PE funds, they can make commitments to invest. Otherwise, investors can adjust their investment portfolios accordingly. From the perspective of business owners, if their companies have the same SIC codes as companies acquired by big-cap companies last year, their businesses are less likely to be acquired by PE firms this year. In terms of finding potential buyers, they should spend more time contacting strategic investors or venture capital firms instead of private equity firms. For stock traders, this information can indicate the increase or decrease of funding in a particular sector, which might affect stock prices.

Appendix A: Demo of the Panel Dataset for Pooled OLS

Sector	Year	PE_Proportion
Energy and Power	2002	0.010152284
Energy and Power	2003	0.023255814
Energy and Power	2004	0.048
Energy and Power	2005	0.071428571
Energy and Power	2006	0.036363636
Energy and Power	2007	0.067961165
Energy and Power	2008	0.046153846
Energy and Power	2009	0.024390244
Energy and Power	2010	0.017857143
Energy and Power	2011	0.09375
Energy and Power	2012	0.046511628
Energy and Power	2013	0.022727273
Energy and Power	2014	0.1
Energy and Power	2015	0.083333333
Energy and Power	2016	0.052631579
Energy and Power	2017	0.15625
Energy and Power	2018	0.242424242
Energy and Power	2019	0.25
Energy and Power	2020	0.105263158
Energy and Power	2021	0.107142857
Materials	2002	0.045454545
Materials	2003	0.170212766
Materials	2004	0.178571429
Materials	2005	0.223529412
Materials	2006	0.205357143
Materials	2007	0.120689655
Materials	2008	0.171052632
Materials	2009	0.162790698
Materials	2010	0.242424242
Materials	2011	0.166666667
Materials	2012	0.254901961
Materials	2013	0.166666667
Materials	2014	0.208955224
Materials	2015	0.163265306
Materials	2016	0.166666667
Materials	2017	0.131578947
Materials	2018	0.236363636
Materials	2019	0.290322581
Materials	2020	0.260869565
Materials	2021	0.24137931
Industrials	2002	0.068181818
Industrials	2003	0.116959064
Industrials	2004	0.152631579
Industrials	2005	0.148717949
Industrials	2006	0.164556962

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