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Premium Price of M&A: The Effects of Low to High Valuation Mergers on Market Value

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ABSTRACT

This paper examines mergers and acquisitions (M&A) activity across different low price-to-book (P/B) industries to high-P/B industries' interactions and the effects on post-deal firm value. I find that acquiring firms ('acquirers') tend to gravitate towards buying target firms ('target') that fall under the abnormal high-P/B category relative to their industry and that the likelihood of acquisition in those high-P/B target firms increases when the acquirer firm itself is overperforming. This study is the first to provide evidence linking acquirers' and targets' relative valuations to acquisition likelihood and post-completion acquirer returns.

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Chapter 1

Introduction

When the COVID-19 pandemic hit, many across the consulting industry thought that companies would slow down on making deals; however, quite the opposite occurred. Over the last few years, deals, whether the divesture of one's company, the acquisition of another, or the merger of another, have accelerated at an enormous pace and are on track to outperform any other fiscal year. In the first half of 2022, despite a slowdown in the second quarter, the US M&A market was still active and growing, making up about 30% of global volume and about 50% of global value (Kengelbach et al., 2022). Across all industries, the technology, financial services, industrials, and energy sectors account for the majority of deals. This may be due in part to the boom that the IT sector has seen in advancing different companies' products, services, and consumer experiences (Rudegeair & Benoit, 2021). Over the last three quarters of 2022, shares of companies that bought another business outperformed the broader global market by more than two percentage points showing the shifting investor outlook on deals rewarding companies for their bold business decisions (Hammond, 2021).

There are several contributing factors believed to be behind the surge in M&A deals during the pandemic including low interest rates, a company's surplus of cash, bullish outlook, and market psychology (PwC, 2023). The recent surge in tech deals raises the question of whether some firms may buy other firms in unrelated industries to attempt to lift the value of the whole acquirer. Despite evidence that SIC industry reclassification (Chen et. al, 2016) and firm name change (Cooper et. al., 2001) occur, to my knowledge, there is no existing evidence on whether acquirers might purchase firms in unrelated industries to try to lift their own valuations.

In Chapter 2, I examine the existing literature on similar phenomenon and patterns in the M&A space. Based on these literatures, I hypothesize that acquirer firms are more likely to buy into a high price-to-book (P/B) valued target firm, and therefore, market evaluations of that acquisition reward the acquirer firm as a whole.

To test this hypothesis, I gathered data from the Compustat, CRSP, and Refinitiv SDC databases and then further combined these datasets to merge company information, financial transactions, and stock price data. Additionally, I classified the firms into demeaned high and low price-to-book buckets to identify those that fall under abnormally high or low-P/B relative to its industry. I then ran a total of three logistic regressions as well as two difference-in-differences regressions to test the effects of varying situations of high-P/B classified or low-P/B classified acquirers buying into high-P/B classified or low-P/B classified target firms and whether or not that affected their quarterly stock returns. The hypothesis, data, and methodology used in this study are discussed in further detail in Chapter 3.

I find that that acquirers tend to engage the most with high-P/B target firms and they are more likely to engage in M&A activity among their own industry classification such as a high-P/B acquirer is more likely to acquire a high-P/B target. This study did not find evidence that acquirers purchasing high-P/B or low-P/B targets earned differentially high or low post-completion stock returns relative to other firms in the same industries and years. Possible explanations for these results may relate to external disruptions to the economy or industry itself that can cause firms to remain within their own value classification when engaging in M&A or internal decisions to acquire influenced by high performance or market survival. The findings from my individual regression models used to estimate these results as well as further potential explanation can be found in Chapter 4.

As the M&A market continues to grow exponentially, the evidence provided by this study adds to the existing literature on M&A activity by looking at the link between firm value and acquisition likelihood. This study's conclusions in addition to potential future research opportunities are discussed in Chapter 5.

Chapter 2

Background

The existing literature on this subject of mis-valuation in the M&A space is not extensive, and so instead, the literature reviewed will focus more on various aspects of the wider available M&A literature such as company mergers, methodology, and some firm valuation analysis. The evidence provided by the existing literature provides valuable insight and foundational research for the topic of domestic market response to firm shifts such as name changes, digitalization, and industry reclassification. This study will look at a more extensive time frame and provide a modernized outlook on market response in regard to M&A valuation activity as most of the current literature reviewed can be viewed as outdated and unrelated.

Primary Related Literature

Two of the primary academic papers utilized for evidence of the artificial inflation of stock prices shed light on ways that firms internally change their company, whether superficial or not, and how the market responds to such actions. The paper “Industry Window Dressing” looks at a mechanism by which investors take shortcuts and present evidence that managers take advantage of through superficial sales management. The basic idea in the paper is that investors sometimes overvalue different segments of the market, and managers can try to take advantage of this overvaluation by tilting their own companies to look more like the types of firms the market is currently overvaluing. The paper examines firms’ selection of a primary SIC code and finds that firms strategically manipulate sales in order to be classified into SIC codes that the market currently highly values. The study analyzed how managers potentially exploited this notion and showed how investors classified “operationally nearly identical firms as starkly different depending on their placement of sales cutoff” (Chen et. al., 2016). Another study looked at an equally superficial change of a firm’s operations during the tech boom of the end of the 20th century and how changing their classified name to add “.com” at the end caused a similar exaggerated market response. The research found that the "dotcom" effect produced an overall abnormal return of about 74% for the 10 days surrounding the announcement day (Cooper et. al., 2001). This study looks to realize a similar engagement with the market, but rather than superficial reclassifications and company name changes, evaluate how a large-scale firm change, such as deal activity affects market value.

The study of “Industry Window Dressing” further found evidence that managers engaged in reclassifying their firm’s activities to realize the large and tangible benefits of the overvaluation of their company by investors. The paper utilized the SIC classification of firm operations which, “designates that each conglomerate firm have a primary industry, determined by the segment with the highest percentage of sales” so firms would manipulate how their sales were classified by this cutoff to be classified under varying industries (Chen et. al., 2016). In “Industry Window Dressing,” they looked at various multi-segmented firms and evaluated what their industry classification looked like and cross-checked this classification by their sales cutoff tactics. They gave the example of a two-segment firm receiving 53% of its sales from technology and 47% of its sales from lumber and is classified as a technology firm, whereas a firm with nearly identical operations receiving the opposite, 47% from technology and 53% from lumber, was a lumber company (Chen et. al., 2016).

In this example, a designated technology company was given significantly higher valuations (i.e., differing investing behavior, sell-side analyst coverage etc.) so they explored how different managers may have manipulated this sales cutoff tactic to their advantage. Their evidence suggests that both current investors and top executives gained large tangible benefits from this industry switching, hence the name “window dressing.” This paper relates to this study through the nature of which companies strategically change internal processes and logistics and how this can affect the valuation of their firm. However, this study aims to look at more than this superficial change of accounting values and dive deeper into how a restructuring of a company can affect the same idea.

In an additional related study, “A Rose.com by any Other Name,” the research follows a similar idea to the former of looking at how superficial changes to a corporation cause significant reactions in stock price. In this case, the paper looks at how the “dotcom” effect produced abnormal returns on the stock price for the 10 days surrounding a company’s announcement day (Cooper et. al., 2001). After the dotcom craze of the late 90s into the early 2000s, the authors on the paper were interested in how various companies began to change the name of their company by adding “.com” to the end of it. In a similar approach and purpose to the former paper, analysts claimed that investors preferred these name changes to appeal to the technology craze of the time and that this bias was heavily reflected in the stock price. Overall, the paper found that when companies changed their name to a dotcom name, they earned significant abnormal returns “on the order of 53 percent for the five days around the announcement date” (Cooper et. al., 2001). The study found that regardless of a company's business's involvement with the Internet, the mere change of name showcased how the market reacted to a superficial company shift. The association with the Internet from the market's standpoint was enough to cause a strong and fairly permanent reaction in the premium of the company's stock price (Cooper et. al., 2001). This article's topic aligned strongly with the foundation of this study through its analysis of how changes within a firm can change the outlook of its overall market value to the larger public. There are several areas of interest I drew from this publication, relating to the researchers' methodology of company categorization as a means of organizing their analysis across varying tiers of firm value. However, my study seeks to look past a firm name change and dive deeper into the M&A/Deals space of this literature space to understand how an internal shift of a merger or acquisition with another firm may over-inflate and cause an artificial premium.

Researchers also saw that this was not a temporary reaction but that it persisted in the stock price of the companies in question. Similarly, to "Industry Window Dressing," this paper offered an insightful understanding of how to measure and evaluate companies' possible overinflated value apart and how to measure the statistical significance of such events (Cooper et. al., 2001). However, it differs that it again looks at a superficial change such as title change or reclassification instead of a change to the entire scope of a company like deal activity. This study hopes to provide more updated research and further this evidence by looking deeper into how companies may be taking advantage of deal trends and why investors and the market may react in exaggerated manners.

Additional Financial Literature

In addition to these more foundational articles of evidence, evaluation of more financially theoretical studies relates to the general literature of financial analysis and methodology of investing. A study looking at ways that investors strategically categorize their risky assets to make portfolio allocation decisions sheds light on classes of investing (Barberis and Shleifer, 2003). The styles discussed in this article relate to how when making portfolio allocation decisions, many investors first categorize these assets into classes of broad nature such as "large-cap stocks, value stocks, government bonds, and venture capital" which helps them allocate these funds across their portfolio. The paper presents a model to assess the importance and usefulness of style investing and its effect on financial markets and security valuation.

Fundamentally, there are similarities between the approach of this paper and the research I intend to conduct; however, this paper differs by looking at a deep-dive into specific asset types and their reclassification effects rather than a larger firm-wide reorganization which this research intends to highlight. In addition, a study on comovement relates to the above's research that looks at an alternative theory of comovement that argues that due to market frictions or noise-trader sentiment, return comovement is delinked from fundamentals. In this research, they decompose the shift in betas around the inclusion of S&P 500 information and find that by applying a univariate analysis they uncover stronger effects, in bivariate regressions the rise in S&P beta is larger than in univariate analysis, and finally that in both univariate and bivariate regressions, the effects are somewhat weaker at lower frequencies (Barberis et. al., 2005).

Another study on irrational market behavior looked to show how factors such as managerial time horizons and financial constraints can affect the optimal hurdle rate for companies. Similar to other research analyzed, Stein looks at contradicting the concept that the stock market is efficient and that there is no way to manipulate stock value at all. In this paper, they state that according to standard finance logic, in an efficient market, the hurdle rate for an investment in any given asset should correspond to the same expected return on the stock in that asset (Stein, 1996).

This is a similar principle to the assumption I will be deriving my research from which is in theory, in an efficient market, when company A valued at $5M buys company B for $1.5M, the combined value should be $6.5M which should be reflected in its stock price, but in reality, this may not be the case. Through this research I hope to identify whether or not there is an artificial premium and possible overinflated value around the announcement date and final deal close that may affect the wider acquiring firm. All of these more theoretically focused studies, look at how variations and imperfections in how the market responds shift the returns of securities that are held amongst investors and my research seeks to identify those artificial returns and value premiums through deal activity (Barberis et. al., 2005; Barberis and Shleifer, 2003; Stein, 1996).

Existing Studies on Firm Value

While there is no extensive literature surrounding this firm mis-valuation post M&A activity, additional studies relating to the other firm changes examine market reaction as an intersection between behavioral finance and financial output to change in company information, behavior, and activity. One study focuses on three key variables to define what 'attention-seeking' is that tracks the buying behavior of individual investors. Similar to this study, there are certain aspects of results that cannot be entirely quantified due to the unpredictable nature of human behavior and public reaction. As stated in a study evaluating the effect of attention-grabbing news, researchers did their best to define that variable in three observable measures: news, unusual trading volume, and extreme returns. Results of this study showed that trading volume in a firm's stock is likely to be higher and individual investors tend to be net buyers on high-attraction days demonstrating the ability to discover abnormal returns based on qualitative subjects (Barber & Odean, 2008).

On a similar vein, Chen and Srinivasan most recently, examine the implications of firm value and performance of nontechnology companies engaging in activities relating to digital technologies. Much of the inspiration for this research came from interest in companies investing much of their assets in the digitalization of their firm and if that had a significant effect on overall market value. In this study, researchers through market-to-book ratio variable analysis and statistical tests on a number of variables found that firms have longer payoffs through digital investments and investors are eager to be associated with companies engaging in advanced technology (Chen & Srinivasan, 2023).

Additional articles relating to mis-valuation as a result of M&A look at the stock market's creation of value to firm stakeholders. One study creates a model to test its research theory by looking at relative valuations of the merging firms and the market's perception of the synergies from the merger (Shleifer & Vishny, 2003). It then further explains who acquires whom, the choice of the medium of payment, the valuation consequences of mergers, and merger waves. Researchers created a simple model of acquisition with the market value of the two firms noted as $V = S(K+K_1)$ with V being market value, S combined equity per unit of capital, and K and K_1 being both firms respectively. Under the assumption that $Q<S<Q_1$, Q being stock market valuation, they calculated total short-run gains and synergy level to find a positive perceived energy and combined positive short-run return (Shleifer & Vishny, 2003). Through further model manipulation and testing under varying assumptions, the study finds that firms have a powerful incentive to get their equity overvalued, so that they can make acquisitions and grow in the market. This research continues to prove that firms will make calculated business decisions to overvalue themselves to make advantageous stock-financed acquisitions. Furthering this research, Savor and Lu address endogeneity problems of stock-financed acquisition research by

creating and testing a sample of mergers that fail for exogenous reasons (Savor & Lu, 2009). In their study, they look to resolve the issue of whether valuation-driven acquisitions benefit or hurt long-term shareholders and answer the question of how stock acquirers would have performed in the absence of the merger. To test this, they researched every failed transaction in the study's selected sample and then created a subsample of those that did not succeed for reasons unrelated to the valuation of the acquirer. This subsample included bids that failed because of regulatory reasons, mostly antitrust interception, competing offers, or unexpected target changes. As a result, the study found that stock acquisitions serve the interests of bidders' long-term shareholders despite any negative announcement or post-event return fluctuations (Savor & Lu, 2009). These papers both examine companies who were arguably overvalued and show that such firms often make these calculated stock-financed acquisitions to buy real assets that will hold their value.

Overall, research like this contributes to the literature on valuation by showcasing how a new aspect of non-accounting changes can significantly drive price and market value for firms. This paper is a part of the continuously expanding empirical literature exploring the possible correlation between firm overvaluation and merger activity. Thus, this examination of M&A activity of firms buying into high valuation industries contributes to the existing literature by looking at cases where acquirers think that purchasing a highly valued target will help their other divisions and overall firm become more highly valued.

Chapter 3

Hypothesis, Data, & Methodology

This section will explain the study's hypothesis, chosen data sets, and the methodology that was used for the analysis. First, this section will define the study's hypothesis, then the sources and application of the data used in the study, the modifications made to the aforementioned datasets to prepare them for analysis, and the analysis itself that generated this study's results.

As mentioned in Chapter 2, there is not extensive financial literature that evaluates firm valuation based on the relative value of acquirers and targets within M&A activity. Much of the existing literature that relates to this study covers firm valuation effects related to other firm shifts such as name change, industry classification, digitalization, buying behavior, or other M&A studies altogether. Across these literatures, much of the research analyzing effect on firm value shows results that market appealing changes to the firm do affect a higher overall value on the firm in question. Given these findings, I hypothesize that acquirer firms are more likely to buy into high valuation target firms and therefore seek a higher value across its business. As such, this study seeks to analyze this effect relative to the classification of the target and acquirer as low or high valuation firms to provide additional research in the M&A and financial literature space.

To test this hypothesis, this study required a few datasets related to M&A activity, firm financials, and market information. In addition, to organize and classify the target and acquirer firms into low and high valuation brackets, I accessed and utilized NYU Stern Professor Aswath Damodaran's datasets for the PE and Price to Book (P/B) Ratio by Industry Sector over the last 20 plus years going back to 1998.

Data Collection

In order to run any regression analysis to test my study hypothesis, there were key pieces of data across M&A activity and company financials that were extensively formatted to prepare to be merged. The final dataset used for analysis is constructed from several database sources: CRSP (Center for Research in Security Prices), Compustat, and Refinitiv SDC (Securities Data Company).

Refinitiv SDC is the principal M&A deal database containing key variables such as announcement date, target and acquirer information, and M&A type. For the purposes of this study, data from SDC was filtered to include only the domestic United States and deals between both publicly traded companies from the years 1977 to 2022. Barring outliers, approximately 17,783 deals across that time period are analyzed in this study. Both CRSP and Compustat datasets provide financial, statistical, and historical market data on thousands of companies. These datasets possess key variables such as firm ticker symbol, stock price, SIC code, quarterly earnings, stock returns, and much more.

The final dataset used in the regression analysis was merged through the STATA platform and the code used to perform the merge can be referenced in Appendix A. Data between CRSP and Compustat was merged on key variables PERMNO (permanent company number) and quarterly returns. An expanded list of variables and definitions can be found in Appendix C. Dates of the data were then formatted to be quarterly for consistency across datasets. Merge of the SDC data and CRSP/Compustat was merged on the ticker symbols associated with each company, both acquirer and target firm. In addition, both the acquirer and target firm's P/B and rank were merged. CUSIP identifiers were considered as a key variable, but in cases where the acquirer or target did not have a real CUSIP identifier, Refinitiv SDC created miscellaneous CUSIPs that would not be translated across the other Compustat and CRSP datasets. Finally, start and end dates were added to the SDC file and one last merge with Compustat and CRSP created the final dataset used in analysis. It is important to note that the SDC database was filtered to keep deals where both the target and acquirer have US tickers that differ from one another. This greatly reduced the size of the sample by eliminating any private deals, but still leaving the sample size well over 1.3M observations of data.

Low and High Valuation Categorization

In addition to the deals and financial data that CRSP, Compustat, and SDC provided for this study, the ancillary aspect of this study and data collection was to categorize the target and acquirer firms into a 'high' and 'low' valuation in the market. In order to define what is an 'abnormally low' and 'abnormally high' valuation firm, industry groups provided by Professor Aswath Damodaran at NYU Stern were used in the analysis. Using Damodaran's Price and Enterprise value to Book Ratios and ROE by Industry Sector datasets, found in Appendix B for reference, price to book value ratios defined as a company's market price per share divided by its book value per share taken from each year from 1998 to 2022. Data from the late 1990s were evaluated to pull key observations during the tech boom/dot.com bubble for firm valuation comparison. Damodaran's industry data sets were the most accessible and comprehensive data which is why they were utilized in this study over individual firm historical P/B ratios.

It is important to note that price to earnings (PE) ratios were considered in place of price-to-book (P/B) ratios for the valuation analysis; however, after conducting the calculations, certain industries were found to have too significant of outliers due to possible economic or environmental factors that negatively affected the overall standard deviation results. Instead, P/B ratios were found to be significantly more consistent and delivered accurate standard deviation calculations.

The final step of categorization was to assign these valuations to the companies listed in the SDC dataset. In order to match any companies with the P/B values of that given year to companies in the final dataset, the key variable SIC (Standard Industrial Classification) codes were used. Damodaran has an Industry Group by Sector dataset, also found in Appendix B, where he compiled industry groups with company SIC codes. However, the issue here is that they are not sorted by year like the P/B ratio calculations are. To prepare the SIC codes for analysis and to merge, each industry's SIC codes, which ranged from about 10 to 40 codes per industry group, were assigned to each year's P/B from 1998 to 2022.

To truly identify which industries are categorically valued significantly above or below their historical valuations, all the P/B data was de-meaned by industry. This process allowed for standardization when selecting unusually high-P/B or unusually low instead of comparing relative to other industries that are naturally considered higher such as technology or lower such as banks. Subsequently, P/B variables were ranked and divided into quintiles and matched based on the firm's corresponding SIC code. Firms were then ranked one through five in each year based on their de-meaned P/B value, with quintile rankings of '1' assigned to firms with an extremely low-P/B and '5' to firms with an extremely high-P/B. From there, binary indicator variables, 'high' and 'low', were created that take the value of one if an acquirer was in the top (bottom) de-meaned P/B quintile in a given year and take the value of zero for all other firm-year observations. This process was repeated for target firms, with the corresponding indicator variables 'hight' and 'lowt.'

Regression Analysis

A logistic regression model was used in this study to evaluate varying effects of abnormally high-P/B and abnormally low-P/B acquirers buying into abnormally high-P/B and abnormally low-P/B targets across multiple tests. The generic regression specification for a logit regression test is:

$$P = \frac{e^{(\beta_0 + \beta_1 x)}}{1 + e^{(\beta_0 + \beta_1 x)}}$$

where P is the probability of success of the independent variables when $\beta_0$and $\beta_1 x$,the independent variables, fluctuate. A difference-in-differences regression model was used to study if the acquirer firm saw a higher return after it acquired a high or low target firm. The generic regression specification for a logit regression test is:

$$y = \beta_0 + \delta_0 d2 + \beta_1 dT + \delta_1 d2 * dT + other\ factors$$

where y is the observed response being measured in each group before and after testing, $\beta_0$and β_1 are the tested independent variables, $\delta_0 d2$ is an indicator binary variable that takes on the value 1 or 0 representing the time period post acquisition, and dT is an indicator binary variable that takes on the value 1 or 0 depending on if an individual firm's acquisition in the tested group falls under the post-acquisition time period. In total, five regression tests were run to evaluate different scenarios of likelihood depending on where both the acquirer or target fell under the ranking of the de-meaned P/B industry categorizations. It is important to note that across all tests run, depending on which outcome was being tested, different variables were chosen as independent — so sample size varies. In general, control variables were outlined as variables ln_saleq, ln_seqq, ln_atq, and ln_ebit that are defined as the natural log of key accounting indicators quarterly sales, quarterly book equity, quarterly total assets, and quarterly EBIT respectively. The log was taken of each so the values of each were closer to normal distribution and were made easier to interpret due to standardization.

The primary variables of interest in these regressions were the binary indicator variables of industry value categorization for acquirer firms ('high' and 'low') and target firms ('hight' and 'lowt'). This is because the de-meaned quintile division allows for focus of the study to be on the two extreme ends of the industry valuation distribution where my hypothesis predicts the biggest effects on firms to be. A continuous measure could also be used in this analysis but is not able to demonstrate the intuitive nature of looking at the extremes of the value rankings. In total, four regressions were utilized to test the probability of predicting different outcome variables regarding acquirer firms.

In regression 1, the dependent variable is 'hight' and in regression 2, the dependent variable is flipped to be 'lowt' with independent variables defined as 'high' and 'low' for both tests. The testing outcome changed in regression 3 to evaluate acquirer firms ('acq'), which takes on the value 1 or 0 if the firm was an acquirer firm as the dependent variable, but with independent variables remaining the same as in test 1 and 2. The fourth and fifth tests differed the most in comparison to tests 1 through 3 by evaluating the dependent variable 'quarterly_return' and new independent variables 'high##post' and 'low##post.' Outcomes of each regression test are outlined in the following chapter.

Chapter 4

Results

This chapter details the findings from the regression analysis outlined in Chapter 3. Findings are overall consistent with the original hypothesis, with some deviations worth noting. Much of the existing literature on M&A and M&A firm valuation support the findings that acquirers tend to see advantageous changes to their firm value after an acquisition is made. This study is the first of its kind to look at M&A activity as a result of the interactions between high and low industry valued acquirers and targets. The results detailed in this chapter continue to support evidence that a high-P/B for target firms and acquirers will cause a greater likelihood of acquisition. These results can be analyzed with the following regression outputs, testing different scenarios of abnormally high and low-P/B valuation firm interaction.

The first two sample results as shown in Table 1-1 and Table 2-1 are outputs of a standard logistic regression test. These tests have the lowest sample size of all tests ran of 13,849 firms due to restricting observations to test only acquirer firms. Regression test 1, referenced in Table 1-1, is trying to understand what characteristics can explain the acquisition of high-P/B target firms. Here, the dependent variable was 'hight', to see if a high-P/B target firm is more likely to be acquired by a high or low acquirer. As seen in Table 1-1, when testing 'hight' against the variable 'high,' there was a coefficient of 2.445381, indicating that there is a strong correlation of high-P/B acquirer firms buying high-P/B target firms. This strong correlation is further shown with a t-statistic of 32.44 and a 95% confidence interval (2.297623, 2.593139). For variable 'low,' there was a coefficient of 0.3236953, demonstrating that although not as strongly correlated as 'high,' there is still a correlation of low-P/B acquirer firms acquiring high-P/B target firms, with a t-statistic of 2.68 and a confidence level (0.0868295, 0.5605611). Results of regression test 1 are statistically significant and show that relative to acquirers with "average" (defined as the middle three quintiles) P/B scores, acquirers with very low and especially very high P/B scores are more likely to acquire high-P/B targets.

The goal of egression test 2, results seen above in Table 2-1, is to understand what the characteristics are that may predict if a firm is acquired. However, the dependent variable was switched to 'lowt' to see if a low-P/B target firm is likely to be acquired by a high or low acquirer. As seen in Table 2-1, when testing 'lowt' against the variable 'high,' there was a coefficient of 0.06778 with a t-statistic of 0.52 and a 95% confidence interval (-0.186756, 0.3223159), indicating that there is statistically not a strong enough of a correlation of high-P/B acquirer firms buying low-P/B target firms. For variable 'low,' there was a coefficient of 2.541237, demonstrating a stronger correlation of low-P/B acquirers acquiring low-P/B targets in relation to 'high.' The t-statistic was 33.07 with a confidence level (2.390616, 2.691858). Results of regression test 2 are statistically significant, and we can observe an inverse relationship to regression test 1.

Table 1-1: High and Low Acquirer Firm, High Target Firm

n = 13,849

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient	Standard. Error	z	P>|z|	[95% Confidence Interval]	
hight						
high	**2.445381**	**0.0753881**	**32.44**	**0.000**	**2.296723**	**2.593139**
low	**0.3236953**	**0.1208521**	**2.68**	**0.007**	**0.0868295**	**0.5605611**
Ln_saleq	(0.107449)	0.042976	(2.50)	0.012	(0.1916793)	(0.232164)
Ln_seqq	0.0804529	0.563124	1.43	0.153	(0.299173)	0.1908231
Ln_atq	0.0823592	0.046097	1.79	0.074	(0.0079893)	0.1727076
Ln_ebit	0.0291	0.0491	0.59	0.556	(0.0677417)	0.1259418
_cons	(4.005029)	0.2118626	(18.90)	0.000	(4.420272)	(3.589785)
LR X^2 (6) = 1320.07						
Pseudo R^2 = 0.1743						

Table 2-1: High and Low Acquirer Firm, Low Target Firm

n = 13,849

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient	Standard. Error	z	P>|z|	[95% Confidence Interval]	
lowt						
high	**0.06778**	**0.1298677**	**0.52**	**0.602**	**(0.186756)**	**0.3223159**
low	**2.541237**	**0.076849**	**33.07**	**0.000**	**2.390616**	**2.691858**
Ln_saleq	(0.0824162)	0.0434474	(1.90)	0.058	(0.1675714)	(0.0027391)
Ln_seqq	0.2791846	0.0571567	4.88	0.000	(0.1671596)	0.3912096
Ln_atq	(0.0100555)	0.0534157	(0.19)	0.851	(0.1147484)	0.0946373
Ln_ebit	(0.0777485)	0.0469223	(1.66)	0.098	(0.1697146)	0.0142176
_cons	(4.371678)	0.2188795	(19.97)	0.000	(4.800674)	(3.942682)
LR X^2 (6) = 1432.21						
Pseudo R^2 = 0.1959						

This next regression test 3 is testing whether a firm is more likely to make an acquisition based on their own P/B industry categorizations of high or low. Here, the dependent variable was ‘acq’ tested against independent variables ‘high’ and ‘low,’ similar to the first two regression tests. The full sample size of 849,572 firms was used for this test. As seen in Table 3-1, with high-P/B firms (‘high’ variable) there was a coefficient of 0.1247188 with a t-statistic of 4.96 and a 95% confidence interval (0.0753912, 0.1740465), indicating that firms are more likely to engage in M&A activity when their own P/B is high. On the other hand, looking at variable ‘low,’ there was a coefficient of -0.0196404 and a t-statistic of -0.75, indicating statistically when a firm is categorized as having an abnormally low-P/B relative to their industry, they are not any more likely or unlikely to engage in M&A activity.

Table 3-1: Likelihood of High and Low Acquirer Firms to Acquire

n = 849,572

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient	Standard. Error	z	P>|z|	[95% Confidence Interval]	
acq						
high	**0.1247188**	**0.0256176**	**4.96**	**0.000**	**0.0753912**	**0.1740465**
low	**(0.0196404)**	**0.0263372**	**(0.75)**	**0.456**	**(0.0712603)**	**0.0319795**
Ln_saleq	(0.0772779)	0.0106735	(7.24)	0.000	(0.0981975)	(0.0563583)
Ln_seqq	0.1011012	0.0141424	7.15	0.000	0.0733826	0.1288199
Ln_atq	0.0952002	0.0116019	8.21	0.000	0.0724609	0.1179396
Ln_ebit	0.1004828	0.0115412	8.71	0.000	0.0778625	0.1231031
_cons	(5.330735)	0.0453953	(117.43)	0.000	(5.419708)	(5.241761)
LR X^2 (6) = 4063.97						
Pseudo R^2 = 0.0287						

Regression 4 follows an Ordinary Least Squares (OLS) regression model which is utilized in this case to test the relationship between one or more independent variables and a dependent variable which in this case is the quarterly return of firms. This test tried to measure how the market responds to M&A activity announcement and whether there is a unique effect dependent on high-P/B or low-P/B acquirer firms. An OLS regression was utilized over a traditional logit regression to eliminate industry level abnormal shock to a firm's quarterly returns. In this test, the sample size is 848,927 firm-quarter observations.

For this regression model, additional binary variables, 'high##post' and 'low##post' were created as a measure of the time period after the announcement date when there was an acquisition. This binary variable was assigned 1 for firms where an acquisition was made 6 years post the announcement date, and all others were assigned a 0. These additional variables help measure if the acquirer firm's quarterly return post acquisition is higher compared to before the announcement of an acquisition was made. It is important to note that variables 'high' and 'low' were omitted from this test's results due to its correlation being statistically 0 to the dependent variable tested.

Observing the regression's outputs referenced in Table 4-1, quarterly returns of firms with a high-P/B statistically stay the same. Similarly, the quarterly returns of firms with low chances of acquisition post announcement date also statistically do not change. Overall, based on regression 4, there does not seem to be a link between a firm's quarterly return and whether or not they engage in M&A activity. This may show that in general, firms are paying a high premium for acquiring another firm, and investors see M&A activity as too financially unstable to reward the firm with an inflation in market value.

The same regression was modeled for regression 5 as test 4, with outputs outlined in Table 5-1. Regression 5 looked to test if the acquirer firm earns a higher return after the announcement of an acquisition of either an abnormally high-P/B target or abnormally low-P/B target firm. In this test, the independent variables were the target firm's M&A activity post announcement date. Target firm's high-P/B and low-P/B categorizations were also omitted from this test's results due to a coefficient of 0. As observed in regression 5's results, both 'hight#post' and 'lowt#post' variables see a negative correlation to the acquirer's quarterly returns, -0.008411 and -0.0049271 respectively, with negative t-statistic values, -2.43 and -1.51 respectively.

These results indicate that no matter which valued target firm is acquired, the acquirer could see decreased quarterly returns which are in opposition to my original hypothesis. This principle may be reflected in the overinflated price that many firms pay to acquire a target firm with abnormally high or low-P/B.

Table 4-1: Quarterly Returns Post Announcement Date

n = 848,927

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient	Standard. Error	z	P>|z|	[95% Confidence Interval]	
Quarterly_~n						
high#post	**0.0019469**	**0.0026686**	**0.73**	**0.466**	**(0.0032837)**	**0.0071775**
low#post	**0.0015648**	**0.0022597**	**0.69**	**0.489**	**(0.0028645)**	**0.005994**
Ln_saleq	0.0048109	0.000923	5.21	0.000	0.0030018	0.00662
Ln_seqq	(0.0098992)	0.0009373	(10.56)	0.000	(0.0117363)	(0.0080621)
Ln_atq	(0.0208174)	0.001152	(18.07)	0.000	(0.0230753)	0.0185594
Ln_ebit	0.0201765	0.0005866	34.40	0.000	0.0190267	0.0213263
_cons	0.1698514	0.0029268	58.03	0.000	0.1641146	0.1755882

$R^2 = 0.0935$

Adjusted $R^2 = 0.0715$

Table 5-1: Quarterly Returns Post Announcement Date, Target Firm

n = 848,927

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient	Standard. Error	z	P>|z|	[95% Confidence Interval]	
Quarterly_~n						
hight	0.0061201	0.0026687	2.29	0.022	0.0008893	0.0113509
lowt	0.0078132	0.00206	3.79	0.000	0.0037755	0.0118509
hight#post	**(0.008411)**	**0.0034653**	**(2.43)**	**0.015**	**(0.0152034)**	**(0.0016187)**
lowt#post	**(0.0049271)**	**0.0032716**	**(1.51)**	**0.132**	**(0.0113398)**	**0.0014855**
Ln_saleq	0.0048029	0.000923	5.20	0.000	0.0029938	0.006612
Ln_seqq	(0.0099024)	0.0009358	(10.58)	0.000	(0.0117367)	(0.0080681)
Ln_atq	(0.0208833)	0.0011513	(18.14)	0.000	(0.0231399)	0.0186268
Ln_ebit	0.020169	0.0005868	34.37	0.000	0.0190189	0.0213191
_cons	0.170045	0.0029204	58.23	0.000	0.1643208	0.1757692

$R^2 = 0.0935$

Adjusted $R^2 = 0.0715$

Potential Explanations for Results

The results previously described, reflect a pattern of M&A activity that acquirer firms tend to gravitate towards high-P/B firms and engage in acquisitions when their own firm is performing well. I observed in the first two regressions that abnormally high-P/B target firms were likely to be acquired by both high and low categorized acquirer firms. We can observe a much stronger correlation between a high-P/B acquirer buying a high-P/B target firm. A potential explanation for this relationship is that a firm is more likely to acquire an abnormally high-P/B target firm, such as an up-and-coming software firm, when its own company is overperforming and doing well relative to the market.

On the other hand, we can see an opposite relationship when testing the likelihood of abnormally low valued target firms being acquired by high or low acquirer firms. Based on the results, low-P/B acquirer firms had a stronger correlation to acquiring low-P/B target firms. This relationship could potentially be explained by significant shocks and disruptions to an industry that can cause acquirer firms to stick to buying within their similar industry. For example, when a firm is underperforming (abnormally low-P/B relative to its industry), the 'low' firm may look to other firms within its industry to improve its business and merge to become a stronger parent company.

The results reflect that high-P/B acquirers are no more likely to buy low-P/B targets relative to average. The most statistically significant findings were between high-P/B acquirers and high-P/B target firms and between low-P/B acquirers and low-P/B target firms. Results between high-P/B acquirers and low-P/B targets also did not produce statistically significant results, but low-P/B acquirers and high-P/B targets did, suggesting a correlation in support of my hypothesis.

In addition, opposite to what was predicted in my hypothesis, this study could not find a correlation to a market response of higher quarterly returns following the announcement date of an acquisition. One explanation for the decrease in quarterly returns for acquirers, is that when buying into either extreme of the industry valuation, it's most likely that an abnormally high or low-P/B target firm cannot provide synergies for the parent firm. Not only may quarterly returns not change, but acquirer firms could potentially see a decrease as well. This may be because when synergies do not align, there are not many costs that both firms can cut or revenue streams to grow. Instead, firms can even incur a greater intake of costs to transition both parent and target firms into one firm, so investors may view these types of abnormally high and low acquisitions as a waste of shareholder value and share price falls.

Overall, this study provides new evidence to firms and future research to look at how acquirer and target firm value affect the outcomes related to M&A activity. These results can continue to further the field of M&A literature by looking at how firm valuation, both for the acquirer and target firm, and market positioning can influence an acquirer firm's decision-making when looking to engage in M&A.

Chapter 5

The Future of the M&A Space

In conclusion, this study evaluates whether abnormally high or low valued firms affect the likelihood of acquisition and, furthermore, if there are any advantages associated with that acquisition. The study expected to find that acquirers tend to engage the most with high-P/B target firms and that by doing so, would see firm wide value creation as a result. The results from this study concluded that acquirer firms are more likely to engage in M&A activity among their own industry classification, such as, a high-P/B acquirer is more likely to acquire a high-P/B target. However, this study was unable to provide statistically significant evidence that firms see quarterly return increases because of market response to the acquisition. The goal of this paper is to provide further research and information in the M&A and firm valuation space by testing the intertwined relationship between varying abnormal firm value of acquirers and targets and acquisition. Outputs from the regression analysis provide evidence of a relationship between acquirers and targets based on their industry value classification.

The study was able to test these factors by utilizing both logistic and difference-in-differences regression models to evaluate changes in acquisition activity, acquirer quarterly returns, and acquisition likelihood across varying levels of industry value. For each regression, different sample sizes were used based on the firms of interest, while control data of accounting indicators were used in each regression. This methodology was applied to all five regression models measuring different abnormal industry values, high and low, and different firm types, acquirer or target. Additional variables were created in both regression 4 and 5, utilizing the OLS difference-in-differences model, as variable indicators of the period post announcement date.

This study is the first of its kind to test the relationship between an acquirer and target's relative value, and it hopes to add to the existing literature on M&A and firm valuation. The findings from this study introduce new questions into the link between firm valuation and M&A activity. The data and findings from this study may be built upon for future research. The data used to create the industry value classifications was collected from Professor Damodaran's online database; however, subsequent studies looking to enhance and home in on firm value can look more specifically at individual firm's historical P/B. Additional research should be conducted to further evaluate the effects of firm value on acquisition likelihood outside of the abnormal industry values. Other opportunities can include looking within specific industries or across two industries of interest and the likelihood of acquisition.

As the M&A market ebbs and flows in response to economic and political changes, more data and information will be required to expand the research in this field. Future insight to understand the patterns of behavior and decisions firms make can reveal how they can greatly influence the market and economy around us.

Appendix A

STATA Dataset Merge Code

CRSP Code

```
use crsp, clear
replace ret = "" if ret == "B" | ret == "C"
destring ret, gen(ret_num)
tostring date, gen(date_str)
gen date2 = date(date_str, "YMD")
gen quarter = qofd(date2)
format quarter %tq

gen double log_monthly_factor = log(1+ret_num)
by permno quarter, sort: egen double quarterly_return = total(log_monthly_factor)
replace quarterly_return = exp(quarterly_return) - 1
duplicates drop permno quarter quarterly_return, force
keep permno comnam date ticker quarter quarterly_return
drop if missing(comnam)
```

Compustat Code

```
use compustat, clear
rename lpermno permno
tostring datadate, gen(date_str)
gen date2 = date(date_str, "YMD")
gen quarter = qofd(date2)
format quarter %tq
drop date_str date2

merge m:1 permno quarter using crsp_edited
keep if _merge == 3
```

SDC Code

```
use sdc_raw, clear

gen announce_date = date(date_announced, "MDY")
format announce_date %td
gen announce_quarter = qofd(announce_date)
format announce_quarter %tq

gen effective_date = date(date_effective, "DMY")
format effective_date %td
gen effective_quarter = qofd(effective_date)
format effective_quarter %tq

drop if announce_quarter < tq(1950q1)

destring year_effective, gen(effective_year)

replace value = subinstr(value,",","",.)
destring value, replace

drop date_announced date_effective year_effective
```

```
drop if missing(target_tic) & missing(target_tic_parent)
drop if missing(acquirer_tic) & missing(acquirer_tic_parent)

gen ticker_acq = acquirer_tic
replace ticker_acq = acquirer_tic_parent if missing(ticker_acq)
gen ticker_target = target_tic
replace ticker_target = target_tic_parent if missing(ticker_target)

keep if ticker_acq != ticker_target

keep deal_num value target ticker_target acquirer ticker_acq announce_date announce_quarter effective_date
effective_quarter type status

sort announce_date target
```

Appendix B

Damodaran Datasets

I. Price and Enterprise Value to Book Ratios and ROE by Industry Sector (By Year):

1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011	2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023

II. Price and Enterprise Value to Book Ratios and ROE by Industry Sector Industry Groups:

- Advertising
- Aerospace/Defense
- Air Transport
- Alternate Energy
- Aluminum
- Apparel
- Auto & Truck
- Auto Parts
- Auto Parts (Replacement)
- Bank
- Bank (Canadian)
- Bank (Foreign)
- Bank (Midwest)
- Banks (Regional)
- Beverage (Alcoholic)
- Beverage (Soft Drink)
- Biotechnology
- Broadcasting
- Brokerage & Investment Banking
- Building Materials
- Business & Consumer Services
- Cable TV
- Canadian Energy
- Cement & Aggregates
- Chemical (Basic)
- Chemical (Diversified)
- Chemical (Specialty)
- Coal/Alternate Energy
- Computer Software & Svcs
- Computer & Peripherals
- Construction
- Copper
- Diversified Co.
- Drug

- Drugstore
- E-Commerce
- Education/Educational Services
- Electric Util. (Central)
- Electric Utility (East)
- Electric Utility (West)
- Electrical Equipment
- Electronics
- Electronics (Consumer & Office)
- Engineering & Construction
- Entertainment
- Entertainment Tech
- Environmental & Waste Services
- Farming/Agriculture
- Financial Services
- Financial Services (Non-bank & Insurance)
- Food Processing
- Food Wholesalers
- Foreign Electron/Entertn
- Funeral Services
- Foreign Telecom.
- Furn./Home Furnishings
- Green & Renewable Energy
- Gold/Silver Mining
- Grocery
- Healthcare Equipment
- Hospitals/Healthcare Facilities
- Healthcare Products
- Healthcare Services
- Healthcare Information & Technology
- Heavy Construction
- Home Appliance
- Homebuilding
- Hotel/Gaming
- Household Products
- Human Resources
- Industrial Services
- Information Services
- Insurance (General)
- Insurance (Diversified)
- Insurance (Life)
- Insurance (Prop/Casualty)
- Internet
- Investment Co. (Domestic)
- Investment Co. (Foreign)
- Investment Co. (Income)
- IT Services
- Machinery
- Manuf. Housing/Rec Veh
- Maritime
- Medical Services
- Medical Supplies Invasive
- Medical Supplies Non-Invasive
- Metal Fabricating
- Metals & Mining (Div.)
- Natural Gas (Distrib.)
- Natural Gas (Diversified)
- Newspaper
- Office Equip & Supplies
- Oil/Gas (Integrated)
- Oil/Gas (Production and Exploration)
- Oil/Gas Distribution
- Oilfield Services/Equip.
- Packaging & Container
- Paper & Forest Products
- Petroleum (Integrated)
- Petroleum (Producing)
- Pharmacy Services
- Pipeline MLPs
- Power
- Precious Metals
- Precision Instrument
- Property Management
- Public/Private Equity
- Publishing
- R.E.I.T.

- Railroad
- Real Estate (Development)
- Real Estate (General/Diversified)
- Real Estate (Operations & Services)
- Recreation
- Reinsurance
- Restaurant
- Retail (Hardlines)
- Retail (Special Lines)
- Retail Automotive
- Retail Building Supply
- Retail (Distributors)
- Retail (General)
- Retail (Grocery and Food)
- Retail (Online)
- Retail Store
- Securities Brokerage
- Semiconductor
- Semiconductor Cap Equip
- Shipbuilding & Marine
- Shoe
- Software (Entertainment)
- Software (Internet)
- Software (System & Application)
- Steel (General)
- Steel (Integrated)
- Telecom (Wireless)
- Telecom. Equipment
- Telecom. Services
- Telecom. Utility
- Textile
- Thrift
- Tire & Rubber
- Tobacco
- Transportation
- Transportation (Railroads)
- Toiletries/Cosmetics
- Trucking/Transp. Leasing
- Unclassified
- Utility (General)
- Water Utility

III. Industry Group by Sector Dataset

Appendix C

Variable List

Variable Name	Variable Description
gvkey	Compustat Standard and Poor's company identifier
permno	Historical CRSP PERMNO Link to COMPUSTAT Record (LPERMNO)
datadate	STATA formatted Announcement Date
conm	Compustat company name
atq	Total quarterly assets
oiadpq	Operating Income After Depreciation - quarterly
saleq	Sales/Turnover (Net)
seqq	Stockholders – Equity Adjustments
sic	Standard Industrial Classification codes
quarter	Reference quarter
date	Announcement date
ticker	Ticker
comnam	CRSP company name
quarterly_return	Firm's quarterly stock return
calendar	Calendar
year	Year
month	Month
ticker_target	Target firm Ticker
announce_date	Announcement date
announce_quarter	Quarter of announcement date
effective_date	Date acquisition is effective
effective_quarter	Quarter of effective date
value	Value
P/B	P/B of acquirer firm
P/B_d	De-meaned P/B of acquirer firm
rank	Quintile rank of acquirer firm P/B value
P/B_target	P/B of target firm
P/B_d_target	De-meaned P/B of target firm
rank_target	Quintile rank of target firm P/B value
high	1 if the firm's P/BV is in the top quintile that year; 0 otherwise
low	1 if the firm's P/BV is in the bottom quintile that year; 0 otherwise
hight	1 for the acquirer if the target firm's P/BV is in the top quintile that year; 0 otherwise

lowt	1 for the acquirer if the target firm’s P/BV is in the bottom quintile that year; 0 otherwise
post	Time period post announcement date
sic_year	Unique indicator for all industry-year combinations
acq	1 if the firm announced an acquisition in the quarter; 0 otherwise
ln_saleq	Natural log of firm’s sales that quarter
ln_seqq	Natural log of firm’s book equity that quarter
ln_atq	Natural log of firm’s total assets that quarter
ln_ebit	Natural log of firm’s EBIT that quarter

BIBLIOGRAPHY

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, *21*(2). https://doi.org/10.1093/rfs/hhm079

Barberis, N., & Shleifer, A. (2003). Style investing. *Journal of Financial Economics*, *68*(2), 161-191. https://scholar.harvard.edu/files/shleifer/files/style_investing.pdf

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, *75*(2), 283-317. https:doi.org/10.3386/w8895

Chen, H., Cohen, L., & Lou, D. (2016). Industry window dressing. *The Review of Financial Studies*, *29*(12), 3354-3393. https://doi.org/10.1093/rfs/hhw020

Chen, W., & Srinivasan, S. (2023). Going digital: Implications for firm value and performance. *Review of Accounting Studies*.

Cooper, M. J., Dimitrov, O., & Rau, P. R. (2001). A rose.com by any other name. *The Journal of Finance*, *56*(6), 2371-2388. https://www.jstor.org/stable/2697826?origin=JSTOR-pdf

CRSP US stock databases. (n.d.). https://www.crsp.org/products/research-products/crsp-us-stock-databases

Damodaran, A. (n.d.). *Useful data sets*. Pages.stern.nyu. https://pages.stern.nyu.edu/~adamodar/New_Home_Page/dataarchived.html

Hammond, E. (2021, October 25). *M&A heads to record $5 trillion year despite, well, everything*. Bloomberg. https://www.bloomberg.com/news/articles/2021-10-25/m-a-deals-head-to-record-5-trillion-year-on-executive-optimism

Kengelbach, J., Friedman, D., Samtani, K., Pot, L., Ruska, T., Keienburg, G., & Degen, D. (2022, October 20). *Dealmaking remains active as dark clouds form*. BCG. https://www.bcg.com/publications/2022/the-2022-m-a-report-dealmaking-remains-active

PwC. (2023, January 16). *Global m&a industry trends: 2023 outlook*. PwC. https://www.pwc.com/gx/en/services/deals/trends.html

Rudegeair, P., & Benoit, D. (2021, September 7). *Deals spree puts banks on track for busiest-ever year*. Wall Street Journal. https://www.wsj.com/articles/deals-deals-deals-banks-feast-on-merger-bonanza-11631007002

Savor, P. G., & Lu, Q. (2009). Do Stock Mergers Create Value for Acquirers? *The Journal of Finance*, *64*(3), 1061–1097. http://www.jstor.org/stable/20487996

SDC platinum financial securities. (n.d.). https://www.refinitiv.com/en/products/sdc-platinum-financial-securities

Shleifer, A., & Vishny, R. W. (2003). Stock market driven acquisitions. *Journal of Financial Economics*, *70*(3), 295-311. https://doi.org/10.1016/S0304-405X(03)00211-3.

S&P Compustat fundamentals. (n.d.). https://www.refinitiv.com/en/financial-data/company-data/fundamentals-data/standardized-fundamentals/sp-compustat-database

Stein, J. C. (1996). Rational capital budgeting in an irrational world. *The Journal of Business*, *69*(4), 429-455. https://www.jstor.org/stable/2353403

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The Pennsylvania State University | Schreyer Honors College — **University Park, PA**
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PROFESSIONAL EXPERIENCE

PricewaterhouseCoopers — **New York City, NY**
Management Consulting Intern | Deals Transformation — *Jun 2022 – Aug 2022*
- Supported Separation Management Office for Fortune 500 client in functional workshop sessions through reflecting next steps and site-specific activities required to close deal resulting in outcome-driven workstream-led action items
- Reconciled key information and data from client deliverables to internal SMO project documents by capturing actionable insights and follow-ups for project and client teams in order to prepare client for smooth transition before deal close
- Produced over 10 internal team and external client documents and deliverables to capture important project milestones and information such as deal timeline, SMO contacts and leads, and deal best practices to assemble pre-client workshops

University Professional and Continuing Education Association (UPCEA) — **Washington, DC**
Research Analyst and Consulting Intern — *Aug 2021 – May 2023*
- Created over 40 deliverable reports for various higher education clients to understand market landscape, recommend new programming initiatives, deliver feasibility analyses, and document important trends across projects
- Compiled white papers, analysis reports, and presentation decks by examining primary survey data and conducting secondary research using databases such as Lighthouse and trend reports to finalize project initiatives for UPCEA clients

Nittany Lion Consulting Group — **University Park, PA**
Engagement Manager — *Aug 2021 – Dec 2021*
- Developed 3 final deliverables through primary and secondary research for non-profit MESA Inc. to increase corporate donors for future fiscal years and integrate new donor retention strategies for their 7,000-member audience
- Administered Qualtrics-designed survey to MESA's 7,000-member audience in order to gather quantitative and qualitative demographic data, understand non-profit's value proposition, and identify opportunity areas for strategy
- Spearheaded 3-member consulting team and managed relations with 4-member client team through organizing weekly client meetings, setting agendas, and creating presentation decks and reports on important updates and deliverables

Associate Consultant — *Dec 2020 – May 2021*
- Identified 50 potential partnerships for startup firm ParaPer4mance across 4 primary industries by providing primary background information and company synergies into an Excel database to grow firm's client and investor portfolio
- Remodeled ParaPer4mance's company pitch deck and produced an approach strategy guide by tailoring pitch deck with key firm and potential partnership alignments to create an accessible way to reach new clients and investors

Vanguard Group — **Malvern, PA**
College to Corporate Business Intern | IIG Participant Services — *Jun 2021 – Aug 2021*
- Recommended 3 programmatic initiatives for Vanguard's Institutional Investor Group contact center of 250 crew members through industry and firm research, data analysis, and benchmarking to increase employee engagement
- Conducted focus group of 20 employees to gather insights and verbatim through discussion topics about departmental performance, employee wellbeing, and company culture to inform and support recommendations
- Reviewed extensive general engagement, industry, and call center research to understand employee engagement

LEADERSHIP EXPERIENCE

Penn State Prime Brand Consulting Club — **University Park, PA**
Brand Director | Nestlé — *Jan 2021 – May 2021*
- Directed brand team of 5 and agency team of 4 in collaboration with Fortune 100 company Nestlé to identify and target a new consumer market for Hot Pockets brand and develop a media and creative strategy to increase buyer loyalty
- Conceptualized final Hot Pockets media plan by identifying key consumer insight to hone in on middle class moms and develop 15 strategic online, in-store, and cross-channel deliverables centered around our key consumer insight

SKILLS, HONORS & INTERESTS

Skills: Conversational Mandarin Chinese, Proficient in Microsoft Office, Qualtrics, WordPress
Honors: 1st Place Deloitte NUCC & Penn State (2021), Carey Lynn DeMoss Memorial Award, Gerald P. & Joyce K. UG Award
Interests: 2D Art, *Bon Appetit*, Crime Shows, Journaling, Nalgene, Nails, National Parks, Running, *Peloton*, Paris, *Trader Joes*