Financial Outcomes of Private Equity-Backed Portfolio Companies Post-IPO

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Undergraduate Honors Thesis

Abstract
ABSTRACT TO GO HERE

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Contents

1 Introduction

My analysis looks to investigate the long-term financial outcomes of companies (portfolio companies or portcos) that were formerly private equity (PE)-backed (strictly buyout-related private equity) in the US by comparing outcomes on a 1–5-year time horizon post-PE exit. The primary vehicle of exit will be an initial public offering (IPO). Through my investigation, I aim to analyze if companies outperform non-PE-back companies after IPO. In doing so, I hope to examine the long-term implications of private equity investment on the portfolio companies that they aim to grow. Since there has been a plethora of contrasting viewpoints surrounding the question of whether private equity involvement ultimately destroys or adds value to portfolio companies on a long term time horizon, I aim to provide further discussion on how companies respond once they are no longer held by the PE firms.

After completion of the first analysis, I look to investigate if portfolio companies are able to sustain the same growth levels post-IPO as they were under private equity control. With this, I aim to further discussions involving implications between Private Equity involvement and long-term portco health. This analysis will be done through the use of an event study where IPO is the event in reference.

For this research, I define the "treated" group as portfolio companies with previous private equity backing, and the "control" group as all other companies that have previously not received backing from PE. Data for this project comes from IPOs of both treated and control IPO events that occurred from 2010 to 2018. My analysis first consists of regressing on propensity scores to assess the causal effect of PE treatment. Since the treatment imposed on private equity firms is non-random, I must first eliminate the bias present in the targeted acquisitions by assigning each company a propensity score to assess their likelihood of being selected as a portfolio company. Some covariates I use include employee count, the number of years a given firm has been in business, and common deal and business multiples. To increase the heterogeneity of my control variables, I will look to target several different industries presently targeted by private equity firms. Companies will be split into their respective industries in accordance with Pitchbook's convention of classifying company sectors. Once companies are successfully matched, I construct a t-test for statistical significance within the treated and controlled populations to test for differences within mean financial metric growth of the two populations. Metrics tested include revenue, EBITDA, net income, liquidity, and ROE growth rates of PE-treated and non-treated companies at one-, three-, and five-years after IPO.

I leverage multiple confirmed sources to construct my analysis. To gain background information about companies, I use S&P Capital IQ. In addition, the source provides accurate valuation multiples, deal data, and company financial statements for public companies. IPO data will be pulled from a combination of both Pitchbook and Capital IQ. Pitchbook specializes in private equity transactions and keeps an extensive log of every pe-backed IPO exit dating back to the late 1800s. Capital IQ, on the other hand, provides extensive data on every IPO on both the NYSE and NASDAQ, as well as all worldwide public exchanges, and will be my primary source for looking at comparable non-PE-backed IPOs. Berkeley students have access to both Capital IQ and Pitchbook for free.

The Security and Exchange Commission (SEC) requires all public companies to register IPOs through publicly available S-1 documents that can be found either on any publicly traded company's website or directly through the SEC. S-1 documents will serve as the primary means of analyzing pe-backed performance pre-IPO as they are required to submit financial documentation prior to IPO. Annual 10-K filings are accessible publicly in the US through the same channels and will be used to analyze the financial performance of public companies post-IPO.

2 Related Literature

Private equity firms raise funds to acquire and manage targeted companies before selling them to hopefully capture large financial returns. Funds are raised from limited partners (LPs), managed by general partners (GPs), and have an average investment period of 7-10 years. Through the investment period, GPs "add value" to said portfolio companies to increase profitability and potentially increase exit valuation. Following the investment phase is a quick withdrawal and divestiture period to disburse profits back to LPs (Chen, 2022). Strategies for divestiture typically include LBOs to sell the business to another private equity firm, sale to a larger company as a bolt-on acquisition or merger, or through public offerings.

Since the emergence of the commercial private equity industry in the early 80s, there have been a plethora of contrasting arguments surrounding the economic impacts of private equity. An early study by Shleifer and Summers (1988) indicated that buyout investors increased their returns by decreasing employee counts and slashing wages. In contrast, Kaplan (1989) argued that incentives like reducing wasteful expenditures and revenue-increasing business decisions were what led to increased operational performance rather than managerial exploitation. Nonetheless, arguments on both sides prevail. As recently as October 2021, Senator Elizabeth Warren claimed that private equity firms "destroy the long-term prospects of the businesses that they buy" (Warren) since they're incentivized to capture short-term profit by ruthlessly cost-cutting and loading portfolio companies up with debt. This claim is further supported by research from Cressy et al. (2011) which found aggressive downsizing in portfolio company employment following post-PE backing. Recent contradictions to this claim, as evident from a meta-analysis by Verbouw et al. (2020) finds that there is a positive effect on PE portfolio companies' operational performance with little to no difference in employment gains.

Although much research has been done to investigate private equity investment impact on operational performance, less evidence exists analyzing the long-term consequences of PE investments. Lerner et al. (2011) found through 472 leveraged buyout (LBOs) transactions that PE backing does not sacrifice long-term investments. Through patenting activity three and five years after initial investment, they find no significant differences in patenting data pre and during PE backing. This study, much like others mentioned, fails to provide any insight into the performance of portfolio companies post-PE exits. After all, most funds look to divest in a reasonable 7–10-year timeline, so assessing what happens to these portfolio companies, and if they can maintain similar levels of growth after PE "treatment", is important to advance the literature surrounding the financial impacts of private equity. Research from Lavery et al. (2022) along with Melo (2014) suggests that the financial performance of PE-backed portfolio companies either did not fare better post-IPO than their non-PE-backed counterparts or underperformed in the long run. However, these studies were conducted using data from UK and Portugal-based companies respectively, and thus cannot be generalizable to the US.

A recent study by Grønberg (2015) does indeed use US-based companies to investigate the question at hand and finds that non-PE-backed companies performed significantly better 36 months post-IPO on an operational basis. The biggest problem with the research, however, was presented in the matching process for non-PE-backed companies to compare against treated portfolio companies. Grønberg manually matched control companies with 50 undisclosed comparable features from PE-backed portfolio companies. There is no mention of any robust technique used to eliminate the effects of confounders such as Propensity scores or restriction besides this manual matching. In addition, the paper uses data from US IPOs from 2002 to 2010. After an extensive search, I was not able to find a similar study that used US IPOs from 2010 to 2018 and so will choose to do so. A study by Athar (2018) does make use of this existing data but proposes a slight variation on the question at hand by investigating the aftermarket performance of portfolio company stock prices post-IPO.

2.1 Differences in Methodologies

Most of the studies that I have presented use some form of matching technique to address the exogenous impact that private equity investments have on portfolio companies. It is crucial to use techniques such as propensity scores or matching in this environment because the selection process of private equity targeted acquisitions is strictly nonrandom. Using existing financial documents on target companies, PE firms can select which firms to invest deemed on their confidence of being able to see a favorable return on investment (ROI). Instead of attempting to perform this match by hand, I leverage propensity scores using a logistic regression to get a probability score for how likely the private equity firm would invest in the control companies I select. Once I calculated the propensity scores for the individual companies, I regress on the propensity score estimates to get a causal interpretation on the effects PE treatment by setting it as a dummy variable. Unlike performing a 1-to-1 matching as in other studies investigated, regressing on PE treatment effects directly without matching companies beforehand allows me to use many more data points than previous research. For example, Grønberg (2015) loses nearly 87% of all portfolio company IPOs to use in their model because they could not find suitable matches for the portfolio companies. Further, the model throws out the vast majority of non-PE-backed IPOs that it was not able to find matches more. From 2010 through 2018, there were roughly 6.8 non-PE-backed IPOs per PE-backed IPO. As I did not want to throw out these data points, I found matching to not be suitable in my model. Adding on to this methodology, I use performance and size metrics pre-IPO of both non-PE-backed and PE-backed companies to serve as covariates for calculating propensity scores. These include, but are not limited to, company age, EBITDA margin growth, liquidity ratios (assets to liability ratio and cash to liability ratio), profitability ratios (gross profit margins and return on equity), and total company employment.

The data set that I use, US companies from 2010-2018 provides a more accurate depiction of US private equity when compared to the other research papers. The most recent paper to do so, Grønberg (2015), leverages data from US IPOs from 2002-2010. Through the two periods mentioned, there has been an increase from 409 transactions to 471 with an increase in the post-valuation median from $468.3M to $777.5M (Pitchbook). With a 15% increase in the number of PE-backed IPOs and a 66% increase in the post-valuation median, it's necessary to use this new dataset to advance findings on the topic.

3 Data Overview

I decided to only use companies from the US to study the impacts of private equity. More specifically, companies selected were either publicly listed on the Nasdaq or NYSE. The timeframe that I chose, company IPOs from 01/01/2010 until 01/01/2018 was selected for three reasons. Firstly, as mentioned, the most recent use of portfolio company IPOs for similar research as mine uses data from 01/01/2002 until 01/01/2010 (Grønberg, 2015). Secondly, I have decided to set an upper cap at 01/01/2018 as to investigate portfolio company IPOs by using at least five years of company performance data post-IPO. Lastly, the period specified saw no recessions in the US economy (recession defined in this paper as two successive quarters of falling GDP). One issue with Grønberg's design was that the data observed did not fully capture the period specified. This was largely due to the Great Recession, which saw virtually no PE-backed exits into the public sector from 2007-2009. Since both IPO and PE activity increased from 2010 through 2018 (Statistica; McKinsey), there is no shortage in data availability in this period.

Company data for my research will be split into different subgroups; private equity portfolio companies that have IPO'd (treatment), non-private-equity-backed private companies with similar IPO dates as my treatment group (control 1), and public companies that were already traded on the market at time of treatment IPO. The timeframe I target only includes date of IPO. For example, multiple data points used go as recent as 12/2022.

3.1 Treatment - Portfolio Company Selection

The selection process for the companies was done using Pitchbook. Pitchbook allows me to set certain flags to filter out companies between the specified dates and location that were involved in private equity-backed exits. Pitchbook also further specifies which companies were involved in VC-backed exits, and which ones were involved in traditional buyout-backed exits, thus saving me time by not having to search for private equity involvement for each portfolio company. This brought the total amount of exited companies to 699. By further specifying the IPO deal stage as "Completed", I was able to narrow the list to 531. In addition, I can filter for transactions where private equity funds will not have a controlling interest post-IPO, which brought the list down to 392. Next, I eliminated all companies in very niched industries that were not primary targets of private equity or considered as sectors. An example of this was my decision to eliminate Special Purpose Acquisition Companies, which do not have any business operations, and private equity firms that went public as they are inherently PE-backed. Adding additional flags to narrow down the companies to just those listed on Nasdaq or NYSE further decreases the total amount of companies to 261.

One initial problem with this dataset is that determining how long a company has been public for is nontrivial. For example, some companies since initial IPO have been acquired or merged with other companies within the observation period of five years. These companies need to be excluded as there is not enough observational data to be useful for my model. Pitchbook writes ticker symbols next to company names that are still publicly traded, so all I must do is look at those without ticker symbols. I am careful, however, to keep companies that went bankrupt within the five-year time horizon. After filtering to make sure that there were enough data entries to use for each portfolio company, the total amount of companies that I use in my model fell to 141. Filtering out companies at this level was simply done by manually googling their trading history and SEC filings. All public company activity must be published in 8-K forms as per SEC requirements, so although cumbersome, eliminating those without five years of public information is simple.

3.2 Control – Non-PE-Backed Company Selection

I use non-PE-backed companies that IPO'd from 01/01/2010 to 01/01/2018 as my control. Pitchbook allows for a search of IPO deals to specify if the companies had no previous IPO involvement. With this flag on, I was able to find 1373 companies with similar search criteria. Public company data is also used to gauge the performance of both PE-backed and non-PE-backed companies to account for average industry growth within the verticals targeted. After eliminating companies that had no private equity involvement whatsoever, did not have the required five years of financials, or were categorized in niche industries such as SPACs, I was left with 953 control companies to work with. As mentioned, the large discrepancy in non-PE-backed and PE-backed IPOs was the reason why it's to use matching. The population sizes of the two groups are drastically different, and therefore, I would have been left with several valuable but discarded data points.

3.3 Post-IPO Company Data

The data used to analyze the difference between treatment control groups is trivial to find. As mandated by the SEC, and the main reason for choosing companies registered on either the Nasdaq or NYSE exchanges, publicly listed companies on NAS and NYSE exchanges are required to report financial reports quarterly with 10-Q forms and annually with 10-K forms (SEC). This information is also made public on the SEC database and, to my knowledge, never expires. Therefore, whether the companies are taken private after the initial IPO or file for bankruptcy, I was able to find financial information on the observed companies long after it is no longer useful.

The metrics of interest are included on balance sheet and income statement within the financial reports. Revenue, Income, and Net Income can be located on the income statement and are found on all 10-K forms that were compiled. Liquidity, measured as cash and cash equivalence at the end of the reported period, is located on the balance sheet. ROE is not genally found on the balance sheet, but is calculated as total liabilities over total equity. The two are required parts of any balance sheet calculation. Due to the time horizons of my study, I use annually-filed 10-K forms for the analysis. Five successive 10-K's will be used after the IPO per each company observed to analyze performance trends.

4 Analysis

Hypothesis 1 (H1) *Company growth rates of PE-Treated companies post-IPO are statistically significant*

Hypothesis 2 (H2) *Portfolio Companies maintain statistically similar growth rates post-IPO*

4.1 Analysis 1 - Analyzing Treated & non-Treated Performance

As previously stated, I rely on propensity score estimates for each company to compute their probability of treatment. My analysis relies on two data tables. The first of which is a deals table that maps companies to their dates of IPO. There were 141 IPO's of PE-treatment firms with sufficient financials to compute a propensity score and 832 IPO's of non-treated firms with the same criteria from 2010 through 2018. Along with these fields were relevant metrics that I used to calculate propensity scores. These metrics include, but are not limited to, ratios such as Valuation/EBITDA, Valuation/Cash Flow, Deal Size/Revenue, Deal Size/Net Profit, and company-specific information such as total years of operation, employee count, and EBITDA margins.

Companies were subdivided into seven industries to address industry-specific effects that could introduce bias in growth rates. The industries include:

```
Business Products and Services (B2B)
Consumer Products and Services (B2C)
Energy
Financial Services
Healthcare
Information Technology
Materials and Resources
```

Private equity activity is highly present in all these industries, as was made evident by deal information from Pitchbook. The second data set is a compiled list of all IPO'd company financials dating from 2010 to 2022. There were roughly 36,000 total company financial reports in the data set. Companies report four times a year, but since many reporting companies report the bulk of their financial metrics in December (Q4) of each year, I relied on end-of-year financial reports for my estimations. Both data sets were pulled from Pitchbook and required a substantial amount of cleaning before working with. For one, many entries in the data were null. To work around this, and not skew the analysis findings, I populate null values with the median of their respective columns and industry. Because I used Python instead of Stata to conduct my analysis, it was required to populated the graph with as many entries as possible. For example, Stata has features in place that will automatically address null values in a data table whereas many Python packages don't respond as gracefully. In addition, my main metrics of interest (revenue, EBITDA, net income, liquidity, and ROE growth rates) were left uncalculated in the dat aset. This required some light data manipulation to calculate. I also found it important to eliminate entries that had extreme outliers. Some companies in the data set experienced large negative decreases in growth rates much higher than other company values, which I suspected would have heavily skewed my analytical findings. All data manipulation directly relating to the format of the data sets was handled through excel. After the data was cleaned, I imported it into a Jupyter Notebook for the remainder of the EDA.

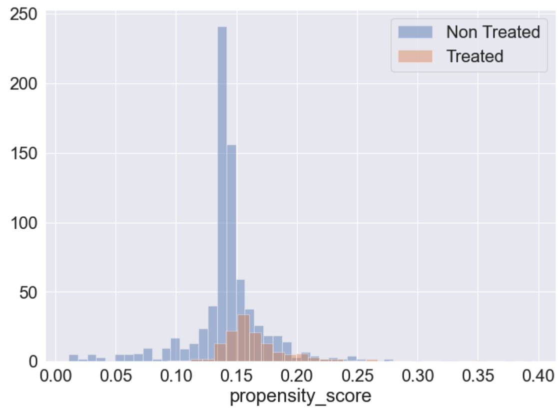

Figure 1: Positivity Check for Propensity Score Overlap

After importing the datasets, I ran a balanced logistic regression on the deal information to compute propensity scores for each respective company, and then appended the propensity scores to the company financial information by mapping propensity scores to company names. An initial positivity check confirmed that none of the propensity scores were less than zero or greater than one, and that there is sufficient overlap to infer causal inference. To compute a two-sided t-test for statistical significance, I ran the calculated propensity scores with a PE-treatment binary indicator, D_i, and ran an OLS regression of the form:

$$Y_{it} = \beta + a_0 D_i + a_1 p_i + \varepsilon_{it}$$

In this model, β, the intercept, is interpreted as the expected growth estimate Y_it given no PE-treatment, $a_0 D_i$ represents the measured PE-treatment effect on Y_it given the company was a PE portfolio company, and $a_1 p_i$ is included as an estimate interpreted as how Y_it will change as company i's likelihood of PE-treatment increases. This regression was calculated using the package `statsmodels.formula.api`, which also gave the option to compute the t-test given the null hypothesis (PE-treatment == 0) as an input. Next, violin plots were graphed to compare the log growth rates of different growth rate measures modeled. Each plot shows the distribution of log values at the one-, three-, and five-years post-IPO increments, and is further subdivided to show how the distributions of PE and non-PE treated companies compared side-by-side at the specified year. Because measures of growth were scattered across a wide range – some companies experiencing 10x growth in the span of one year – it is necessary to take log estimates to get a better view of the overall distribution. All growth distributions can be found in 6.1.

4.1.1 Propensity Scores

The problem with directly investigating the difference between treated portfolio companies post-IPO and non-PE-backed companies post-IPO is that I must account for the exogenous treatment of private equity investment into a company. To address for the selection bias of treatment, which are characteristic of observational studies, I must first attempt to assess the likelihood of both treated and non-treated groups being chosen as a portfolio company by using propensity scores. Propensity scores attempt to address the effect of treatment on a certain group by controlling for covariates that help to predict treatment of a group. By controlling for covariates that affect the probability of treatment, I'm able to control for the probability of treatment itself (Mostly Harmless Econometrics, 60). Once calculating the probability of treatment (propensity score) for both treated and control groups, I can simply regress upon the scores themselves to control for variables I believe to impact company selection.

The initial assumption of the propensity score method is that treated groups can be compared to non-treated counterparts once conditioned on observational covariates (World Bank). The second is that there is a large enough data set within the two groups to run the propensity score estimates on. Prior to running the model, I subdivide treatment and control groups into the industry sector buckets mentioned. I will then further subdivide based on the year of IPO. By separating groups this way, I aim to eliminate any fixed time effects between treatment and control companies. During 2010-2018, there have been numerous regulations implemented which I expect to affect performance of the observed companies. For example, the Tax Cuts and Jobs Act (2017) substantially cut corporate taxation of several businesses, and as a result may have sparked artificial growth in company profits.

Due to metric availability, covariates that I will be regressing on include company age, mean management years of experience, liquidity ratios (assets to liability ratio and cash to liability ratio), profitability ratios, total company employment, low relative capital expenditures, and profit margins. These covariates were chosen because they are key areas of interest that PE funds look for when investing in a company (Consero) but are unlikely to affect my outcomes of interest. Although adding too little covariates to regress on could violate the unconfoundedness assumption, I will be careful to not include too many as it could lead to very low propensity score estimates (World Bank).

The most common approach for calculating propensity scores is a logistic regression. I use a dependent variable $D = \{1 \text{ if PE treatment}; 0 \text{ if no PE treatment}\}$ to identify if the companies received PE-backing or not and calculate my propensity score as:

$$e(x) = \hat{Pr}(D = 1 \mid X = x) = \sigma(\theta x)$$

where x is the vector of covariates used to match groups. The function $\sigma(\theta x)$ is a sigmoidal function which commonly used in logistic regressions. Within the regression, θ is interpreted as a vector of coefficients where θ_i is the expected log odd of having the treatment variable D change due to a change in an additional x_i.

4.1.2 Independent Two-Sample T-test

Once companies scores are calculated, I run a two-sample t-test for statistical significance assess the difference in mean performance indicator growth between treated and control groups. Performance variables of interest, revenue growth, return on equity growth, EBITDA growth, net profit growth, and liquidity growth, are tested to check for statistical significance in my dummy treatment variable. These performance indicators were specifically chosen because they are commonly used in assessing the health of businesses (Twin, 2022). The same package that I use to run my OLS regression has a built-in `results.t_test('hypothesis')` features, which I use for my analysis. The hypothesis in this case is simply the null hypothesis of my analysis. In this case, it would be that PE-treated companies do not differ from their non-treated counterparts when it comes to business growth. Simply put, the hypothesis in this model checks if the dummy variable PE treatment == 0.

In this model, I am investigating company i's performance in year t. The outcome of interest of companies per variable then becomes:

$$Y_{it} = \{Y_{1it} \text{ if } D_i == 1; Y_{0it} \text{ if } D_i == 0\}$$

Setting the average treatment effect to be $E[Y_{1it} - Y_{0it} \mid t] = \lambda$, I can further break down $Y_{it} = \lambda_t + s_t + \delta D_{it} + \varepsilon_{it}$ where $E[\varepsilon_{it} \mid t] = 0$. I expect λ in my model to equal the mean causal effect in financial outcomes between private equity backing pre-IPO and non-PE-backing. Time-fixed effects (λ_t), are used to address time-specific effects that arise from changes in the economic environment from year-to-year. Industry-specific fixed effects (s_t) capture the differences in growth and regulations from one industry to another. After estimating the mean causal effect in treatment, I can plug my result into the t-test model to test for statistical significance.

4.2 Analysis 2 - Testing Performance Post-IPO

After analyzing the differences between both treatment and control groups. I analyze my secondary topic to see if the growth of portfolio companies is sustained post-IPO. This will be done through an event study. The event analyzed here is IPO exit after PE investment. Event studies are used primarily to determine how a certain event impacts the performance of a firm, and thus fit well for this analysis. As stated previously, S-1 documentation shows three years of available company finances before IPO, as mandated by the SEC. Because of this, the timeline of the event study will be from three years pre-exit until five years post-exit. This timeline is purely based on availability of data.

Considering that many companies only report one year of company financials pre-IPO in S-1 filings, the true range of data will vary from one to three years pre-IPO. Five years of post-exit data will be taken from 10-K forms. Growth variables analyzed will be the exact same as the ones analyzed in significance testing above. These include revenue growth, return on equity growth, EBITDA growth, net profit growth, and liquidity growth. The model formula is written as

$$Y_{it} = \alpha_i + \lambda_{st} + \Sigma_{j=-3}^{5} \theta_j \mathrm{D}_{it}^{j} + \varepsilon_{it}$$

where Y_{it} is the performance growth variable measured from company i, α_i is the firm fixed effect, λ_{st} is the year-industry fixed effect, θ_j is the captured effect j years post-exit, D^j_{it} is an indicator function $\{1 \text{ if } j > 0; \text{ else } 0\}$, and ε_{it} is random error. After performance variables are measured, averages of yearly performance are computed, and then in a similar fashion as the analysis 1 design, a t-test is conducted to test whether the growth sustained during private equity treatment statistically differs from growth seen post-IPO. Utilizing t-tests for event study designs is a common practice. To test for significance between the projected growth metrics and reported actual growth post-exit, I use a one-sample t-test for each of the companies for each growth metric tested. After running a one-sample t-test for each of the companies, I compile the results into one table and then proceed to run another one-sample t-test on top of the results to test average sustainability of growth metrics. By testing for significance of returns post-exit, I can determine is growth was sustained, fell, or increased in relation to when the portfolio companies were under PE-management.

The execution of the event study was largely adapted from an in depth resource provided by Princeton University Library which guides readers to replicate event studies in Stata. I maintain the overall structure of the analysis, but both adapt it to run in python and generalize the approach to work for several companies. The process is broken into six stages including Data Preparation, Calculating the Event Window, Estimating Normal Performance, Calculating Abnormal Returns, Testing for Significance, and Generalizing Across All Companies Tested. I build the model first for one of the portcos at random, namely GoDaddy, and then build in functionality to support the remaining companies. To manipulate data throughout the different sections of the event study, python functions were implemented in order to modularize the manipulation and increase reproducibility of the results.

4.2.1 Data Preparation

Data preparation was largely trivial given that the event study uses the same data as my propensity score analysis. The company data was already made available given the earlier model that I built, and so what was left now was to split up the financials on a yearly basis based on the years out from IPO.

4.2.2 Cleaning the Data and Calculating the Event Window

Since the data was already cleaned during Analysis 1, the next step was to calculate the event window. Given the limited timeline, I rely on the interval of years of $-3 < year_i < 5$ where $year_i$ represents the years since the IPO. The data tables used provide the data of IPO exit for each company as well as the date of the selected financials. Leveraging these datapoints, the data is then parted into two sections. The first, entitled `estimation_window`, represents the financial data from $0 - 3$ years before the IPO event. The second, entitled `event_window`, represents financial data from $1 - 5$ years after the IPO event. Through the analysis, portcos will be filtered to make sure that there are enough datapoints to train the model before making predictions. As a baseline, I set a hard requirement of having three years of data make available pre-IPO to have sufficient data for training.

The amount of data rows available for any given company is variable. Some companies may or may not reported three years of prior financials, while other companies may have transitioned from public-to-private or have gone bankrupt within the five years post-IPO. GoDaddy luckily had data from three years prior to five years post IPO, which makes it a perfect candidate the build the model.

4.2.3 Estimating Normal Performance

Normal performance was estimated by training a linear model on the estimation window in order to assess what the predicted growth rate of GoDaddy (later generalized into all companies) would be if the company never IPO'd. In theory, this would give an estimate of the company's trajectory going forward given how quickly or slowly the company had been growing in the past. This is done using a simple ordinary least square (OLS) regression provided from the `statsmodel` python package. A model is made for each one of the estimates in the analysis.

Similar to Analysis 1, regressors (X) used to predict estimates (Y) were selected based on what are believed to go in hand with company growth performance but would not add potential collinearity to the model. Defined below are the column names of the regressor variables as well as the column names for the estimates.

```
X := ['Gross Profit', 'Diluted EPS', 'Cash Dividends Paid',
      'Debt to Equity', 'Stock Price', 'Price to Tangible Book Value']
Y := ['ROE % Growth', 'Revenue % Growth','EBITDA % Growth',
      'Net Income Growth', 'Liquidity % Growth']
```

4.2.4 Calculating Abnormal and Cumulative Abnormal Returns

Once the model was trained on data from the estimation window, growth estimates can then be predicted for each of the regressors per year in the event window. After creating predictions per growth estimate per year, I then calculate the difference in estimations between the predicted growth and what was actually reported for a given year by subtracting the prediction from the actual growth estimate. Differences per year are then summed into one variable and repeated for each growth variable. By doing so, I can track how far off my models were from what was reported.

4.2.5 Testing for Significance

After differences are calculated and summed, I test for statistical significance between the predicted and actual growth variables by using a one-sample, two sided t-test. The test for each model is of the form:

$$tstat_i = \frac{\mathrm{E}[\mathrm{D}_i]}{\frac{\sigma(\mathrm{D}_i)}{\sqrt{n}}}$$

Where D_i represents the summed differences in estimation for variable i and n represents the amount of years of company data available within the event window.

4.2.6 Generalizing the Model and Testing Across All Companies

After building the model for GoDaddy, the last step is to generalize the process over the remaining portcos and aggregate the results into one model. After aggregating, another one-sample t-test is then ran again on the aggregated company t-tests to determine if growth is sustained for the portfolio companies following the IPO exit.

Of note in this stage is the fact that roughly 2/3 of the portcos either did not have sufficient pre-IPO data to train the model, or were missing several data points which made it difficult to make accurate predictions. Filtering for these, the total amount of companies that were suitable to work with fell from 124 to 54.

5 Results

5.1 Analysis 1

Through my analysis I investigate differences in revenue, EBITDA, net income, liquidity, and ROE growth rates of PE-treated and non-treated companies at one-, three-, and five-years after IPO. I find no statistical significance in revenue growth, net income growth, and ROE growth. However, I do find statistical significance in both liquidity and EBITDA growth. These results go in hand with the business model of private equity firms. Firms raise as much debt as possible when acquiring businesses, and thus the cash at hand (liquidity) that these companies will have to pay off debt is directly impacted by the amount of debt they take on. For each growth measure of growth tested, I compile my results in the form of an attached table and violin plot to demonstrate the distribution of data between treated and control groups.

5.1.1 Revenue Growth

From table 1 we can see that there is no significance between previous private equity backing and revenue growth at one-, three-, and five-year time horizons after IPO. At the one-year horizon, I report an estimated PE-treatment impact of -0.821% on total revenue growth with a standard error of 5.313 and t-statistic of -0.156, which is insignificant at the 0.1 level. The reported 95% Confidence interval of the estimates (-11.255 - 9.602) includes 0 and therefore it cannot be concluded that there is significance in revenue growth at the one-year level. The same is seen at three- and five- year time horizons for revenue growth. Three-year estimates found the impact of private equity treatment to be -4.9920% growth

	Revenue Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	28.248***	15.641***	20.326***
	(4.653)	(4.397)	(4.931)
PE	-0.826	-4.992	-0.267
	(5.313)	(4.981)	(5.667)
Propensity Score	-19.081	-7.829	-25.633
	(27.742)	(26.391)	(29.441)
Observations	796	709	619
R^2	0.001	0.002	0.001
Adjusted R^2	-0.002	-0.001	-0.002
Residual Std. Error	53.483(df = 793)	46.902(df = 706)	49.286(df = 616)
F Statistic	0.264 (df = 2.0; 793.0)	0.594 (df = 2.0; 706.0)	0.386 (df = 2.0; 616.0)
Test for PE Significance			
PE	-0.8261	-4.9920	-0.2668
std err	5.313	4.981	5.667
t	-0.156	-1.002	-0.047
P> |t|	0.876	0.317	0.962
0.025	-11.255	-14.770	-11.395
0.975	9.602	4.786	10.862

*p<0.1; **p<0.05; ***p<0.01

Table 1: Test for PE Significance with Revenue Growth %

with a standard error of 4.981 and t-statistic of -1.002 which five-year estimates found an impact of -0.2668% growth with a standard error of 5.667 and t-statistic of -0.047. We fail to reject the null hypothesis of no statistical PE-treatment impact on all years measured. Although nothing can be statistically concluded with these estimates, it appears to be the case that portfolio companies could in fact be growing at a slower pace than their non-treated counterparts. This is made evident in Figure 2 where we can see that log growth rate distribution peaks appear to be slightly lower than non-treated counterparts at all years measured. Of note as well is the long upper bound tail of non-treated companies and long lower bound tail of portfolio companies. Through the tails we can see that there is greater concentration of very high growth measures in non-treated companies and vise versa for the portfolio group.

5.1.2 Net Income Growth

	Net Income Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	2.741	3.713	39.763
	(31.430)	(53.466)	(37.912)
PE	21.676	-73.491	-48.050
	(36.631)	(59.385)	(44.697)
Propensity Score	-77.826	-36.058	-70.860
	(187.379)	(324.489)	(227.394)
Observations	769	699	617
R^2	0.001	0.002	0.002
Adjusted R^2	-0.002	-0.001	-0.001
Residual Std. Error	358.925(df = 766)	553.827(df = 696)	381.191(df = 614)
F Statistic	0.238 (df = 2.0; 766.0)	0.804 (df = 2.0; 696.0)	0.661 (df = 2.0; 614.0)
Test for PE Significance			
PE	21.6757	-73.4909	-48.0504
std err	36.631	59.385	44.697
t	0.592	-1.238	-1.075
P> |t|	0.554	0.216	0.283
0.025	-50.233	-190.087	-135.828
0.975	93.584	43.105	39.728

*p<0.1; **p<0.05; ***p<0.01

Table 2: Test for PE Significance with Net Income Growth %

In Figure 3 we see less evidence of a difference in overall distribution ranges for both groups. As was the case with revenue growth, there is no statistical significance in PE-treatment impact at any of the time horizons measured post-IPO. One year post IPO, non-PE-backed companies measured on average saw 2.74% growth in net income in the first year after their IPO. The estimated impact of PE-treatment was 21.68% increase in net income with a standard error of 36.631 and t-statistic of 0.592, which is well above the 0.1 significance threshold. At years three and five, we see a slightly different picture with insignificant findings. At year three, companies on average saw an increase of 3.71% in net income growth while PE-treated companies saw nearly 70% decreases in net income growth from the year prior. The standard error measured was 59.39 with an insignificant t-statistic of -1.24. At year five, we see non-PE-backed companies on average seeing increases in net income of 39.76% while PE-treatment suggests a decrease in net income growth of 8.29% with a standard error of 44.697 and insignificant t-stat of -1.075. Since in all three 95% confidence intervals the value of 0 is present, I conclude my failing to reject the null hypothesis as well.

5.1.3 EBITDA Growth

		EBITDA Growth %	
	(Year 1)	(Year 3)	(Year 5)
Intercept	-39.986***	-4.624	2.420
	(12.904)	(11.526)	(13.570)
PE	52.809***	11.185	38.303**
	(14.894)	(13.180)	(15.870)
Propensity Score	181.489**	36.565	20.129
	(77.357)	(69.329)	(81.317)
Observations	794	711	621
R^2	0.025	0.002	0.010
Adjusted R^2	0.023	-0.001	0.006
Residual Std. Error	148.766(df = 791)	123.105(df = 708)	136.787(df = 618)
F Statistic	10.156*** (df = 2.0; 791.0)	0.568 (df = 2.0; 708.0)	3.014** (df = 2.0; 618.0)
Test for PE Significance			
PE	52.8093***	11.1846	38.3031**
std err	14.894	13.180	15.870
t	3.546	0.849	2.414
P> |t|	0.000	0.396	0.016
0.025	23.573	-14.692	7.137
0.975	82.046	37.061	69.469

*p<0.1; **p<0.05; ***p<0.01

Table 3: Test for PE Significance with EBITDA Growth %

In contrast to a first look at the distribution in Figure 4, I find statistically significant results for EBITDA growth at one- and five-year time horizons. The distribution shows us that for both portfolio and non-treated companies within years one and three, most companies tested experienced high levels of growth (between 10-40%) with non-PE backed companies being slightly more skewed toward to upper bound. The mean EBITDA growth rate for non-treated companies one year after IPO was found to be -39.99% while PE-backed companies saw increases of around 12.82% in EBITDA with a standard error of 14.89. The t-statistic of 3.546 is seen to be highly statistically significant at the 0.1, 0.05, and 0.01 p-values.

One reason for this statistically significant increase could relate to the business model of portfolio companies pre-IPO. Private equity firms raise large amount of debt to fund transactions in order to see maximum internal rate of returns. An increase in EBITDA post-IPO could suggest an attempt for the companies to cut cost and raise liquidity so as to pay down the significant debt. At year three post-IPO, we find insignificant results. On average non-PE-backed companies see EBITDA growth rates of -4.62%, while PE-treated companies on average saw 6.56% increases in EBITDA with a standard error of 13.18 and t-statistic of 0.849. If my first claim of portfolio companies cutting costs to pay down debt at the first year holds, an insignificant result at year three could suggest that the majority of raised debt is paid off at three years post-exit and that portfolio companies no longer need to aggressively cut costs to pay back debt.

Interestingly, I also find significant results at the five-year horizon. Non-treated companies saw increases of 2.42% on average which treated ones saw an additional 38.30% growth on average. Standard error was measured to be 15.87 and the t-statistic of 2.414 is statistically significant at p-values of 0.1 and 0.05. For years one and five post-IPO we reject the null and conclude that PE-treatment does cause statistically significant EBITDA growth at these horizons.

	Liquidity Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	101.415**	297.336***	111.414***
	(43.578)	(72.788)	(42.626)
PE	-49.482	-160.929**	-54.027
	(49.769)	(81.487)	(50.103)
Propensity Score	184.530	-429.127	10.175
	(259.695)	(442.528)	(255.370)
Observations	784	705	618
R^2	0.002	0.008	0.002
Adjusted R^2	-0.001	0.005	-0.001
Residual Std. Error	498.492(df = 781)	757.153(df = 702)	427.190(df = 615)
F Statistic	0.675 (df = 2.0; 781.0)	2.730* (df = 2.0; 702.0)	0.583 (df = 2.0; 615.0)
Test for PE Significance			
PE	-49.4817	-160.9290**	-54.0270
std err	49.769	81.487	50.103
t	-0.994	-1.975	-1.078
P> |t|	0.320	0.049	0.281
0.025	-147.179	-320.917	-152.420
0.975	48.216	-0.941	44.366

*p<0.1; **p<0.05; ***p<0.01

Table 4: Test for PE Significance with Liquidity Growth %

5.1.4 Liquidity Growth

In table 4, I find statistically significant liquidity growth at year three post IPO for portfolio companies. At the first year after initial IPO, non-PE-backed companies on average saw liquidity growths of 101.42% while portfolio companies saw increases of 51.93% in liquidity. The measured standard error of PE treatment was calculated to be 49.769 and the t-test showed insignificant results at a p-value of 0.1. At year three, we see a mean effect of private equity treatment to be 160.93% less liquidity growth compared to the estimated 297.34% increase in liquidity of non-treated companies. Standard error was measured to be 81.49 with a t-statistic significant t-stat of -1.975 at p-values of 0.1 and 0.05. Lastly, there is no statistical different between treated and non-treated companies at year five post-IPO, which suggests there being no impact on liquidity growth of PE-treatment on a longer timeline. Estimated growth of 111.41% was seen in non-treated companies while portfolio companies saw on average 53.38% increases in liquidity. Interestingly, portfolio companies were seen to have less liquidity growth on average than their non-treated counterparts. In theory, we would expect this to be due to portfolio companies paying off debt from initial PE financing, but this cannot be inferred.

5.1.5 ROE Growth

		ROE Growth %	
	(Year 1)	(Year 3)	(Year 5)
Intercept	-100.720**	-68.770	-55.532
	(47.254)	(46.276)	(49.299)
PE	-55.781	-29.781	-13.531
	(54.922)	(53.241)	(57.936)
Propensity Score	231.437	229.069	189.768
	(281.532)	(277.472)	(295.475)
Observations	781	698	614
R^2	0.002	0.001	0.001
Adjusted R^2	-0.001	-0.002	-0.003
Residual Std. Error	544.309(df = 778)	490.600(df = 695)	493.970(df = 611)
F Statistic	0.770 (df = 2.0; 778.0)	0.444 (df = 2.0; 695.0)	0.222 (df = 2.0; 611.0)
Test for PE Significance			
PE	-55.7806	-29.7808	-13.5306
std err	54.922	53.241	57.936
t	-1.016	-0.559	-0.234
P> |t|	0.310	0.576	0.815
0.025	-163.594	-134.314	-127.308
0.975	52.033	74.752	100.247

*p<0.1; **p<0.05; ***p<0.01

Table 5: Test for PE Significance with ROE Growth %

There was no measured significant changes in ROE growth between treated and non-treated companies at any of the years measured. At year one, non-treated companies saw 100.7% decreases in ROE while PE-treated companies saw an additional 55.78% decrease on average. The measured t-statistic of -1.016 was insignificant at any p-value. In years three and five we see something similar. Non-treated companies experienced 68.77% and 55.53%

decreases in ROE respectively while portfolio companies saw additional decreases of 29.78% and 13.53% on average with insignificant t-stats of -0.559 and -0.234 respectively. Due to insignificance in the findings, we fail to reject the null hypothesis and conclude that there is no statistical significance between treated and non-treated companies.

5.2 Retesting Analysis 1

Evaluating the quality of my findings, I was unconvinced by the end results. To either solidify my findings or nullify my initial position, I sought to improve my model by introducing new python packages and data that I had previously excluded.

The initial company financial dataset pulled from Pitchbook that I used throughout my analysis comprises of 36,000 rows of company quarterly financials with 77 columns of either normalized or actual key company data and ratios. As mentioned, although it was the most comprehensive data table that I had access to, there were also omitted data challenges that I attempted to mitigate at both row and column level by excluding and adding data, respectively.

For several of the companies that were tested, Pitchbook only had access to a handful of quarterly financials per year prior to IPO and occasionally did not have four quarters of information on company financials per year post IPO. To work around this, I initially thought it best to merely take one quarter out of the year when most companies statistically release quarterly financials (December) to minimize the total amount of years to exclude from the research. What this didn't account for, however, was the fact that many companies experience seasonality from quarter to quarter. My initial analysis made no attempt to account for this seasonality, or the fact that many companies do not have fiscal years that fall in line with the calendar year (having Q1 start in June, etc.), and thus could be potentially biased toward companies that see their most favorable financials within Q4 of the calendar year. To both counteract the seasonality and include all the quarterly data that I had available, I instead decided to take quarter data per year of each company and average the results given the amount of quarterly information available in order to correct for seasonality and include more rows into the model.

Mitigation of missing column data for the most part remained the same. One thing of note was the fact that since I now computed averages of quarterly financials by year, some of the missing columns that I had were no longer present. For example, upon an initial investigation of the dataset, I noticed that certain company metrics (EBITDA, etc) would only get reported in one quarter of the year. By averaging, many of those row cells were now filled.

5.2.1 Introducing Industries into the Model

Contained within the dataset was qualitative data of company industry breakdown for each company. Industries within the model are included in the column labeled entitled `Primary Industry Data`. To capture industry data within the propensity score estimations, I one-hot-encoded the column in my data set and drop one of the encoded columns to make sure there is no collinearity occurring. The reason for this is because parameters such as financial ratios are likely to change from group to group, but stay fairly consistent within the same group. For example, historical trends within acquisitions have shown that enterprise value/EBITDA (EV/EBITDA) of tech companies, an industry with high growth potential, is likely to have a higher average ratio than that of retail companies. Controlling for the effects that different industries may have on these ratios is critical to standardizing the companies by controlling for their differences that I see can potentially have an effect on the outcome of the analysis.

5.2.2 Relevance of Propensity Score Matching Regressors

The initial analysis also suffered from weak propensity scores. As evident in Figure 1, propensity score calculations of both non-treated and treated companies were distributed well off the center we'd expect of 0.5 – data for treated and non-treated companies were previously centered around 0.15 in the initial analysis.

Hidden from the first analysis as well was the removal of upper bound and lower bound propensity scores. The initial calculation showed a bimodal distribution which was also centered around 0. Inspecting which of the companies were at this 0 bound, it became clear that the companies had several datapoints missing in the financials, and thus gave a skewed prediction. Adding more covariates to the model helped increase the mean propensity score of the companies, which was interpreted as the model providing better results. The exhaustive list of covariates include:

	count	mean	std	min	25%	50%	75%	max
Revenue	953.0	1622.255467	1.155145e+04	-1.000000e-02	11.21	95.570	420.57	201487.00
Gross Profit	953.0	423.973127	3.685990e+03	-3.331200e+02	62.33	91.970	141.54	107400.00
Net Income	953.0	245.856747	6.858894e+03	-3.969000e+03	-23.05	-2.790	11.26	211400.00
EBITDA	953.0	107.483033	5.984562e+02	-3.129000e+03	-12.88	1.200	58.28	10539.00
EBIT	953.0	66.582802	5.646882e+02	-3.129000e+03	-17.88	-0.790	36.57	9742.00
Total Debt	953.0	828.742581	6.352034e+03	0.000000e+00	1.88	20.000	275.00	145670.00
Valuation/Ebitda	953.0	113.281920	5.022078e+03	-6.000000e+04	-11.82	-4.600	6.73	139081.50
Valuation/EBIT	953.0	-177.679916	4.210747e+03	-1.144972e+05	-14.69	-6.995	7.63	9485.89
Valuation/Net Income	953.0	508.281186	1.826203e+04	-1.144972e+05	-17.37	-8.870	2.81	551156.00
Valuation/Revenue	953.0	-371593.124292	1.030262e+07	-3.156963e+08	3.25	4.600	6.55	446446.00
Valuation / Cash Flow	953.0	483.662823	1.671728e+04	-8.708300e+04	-11.30	12.390	34.33	501842.00
EBITDA Margin %	953.0	-487.575792	4.426103e+03	-8.378402e+04	-8.43	0.000	12.70	1406.00
Employees	953.0	782.421826	5.101035e+03	3.000000e+00	275.00	275.000	275.00	93000.00
Years Since Founding	953.0	21.464848	3.269173e+01	0.000000e+00	5.00	10.000	19.00	191.00

Figure 2: Summary of Updated Pscore Statistics

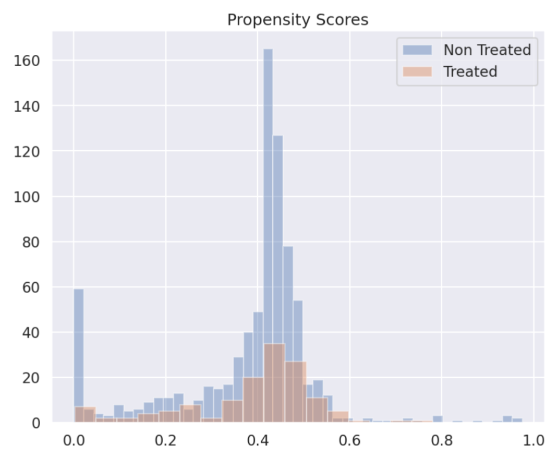

Figure 3: Updated Propensity Scores

Using these updated covariates, we can see that the propensity score distribution significantly increases from centered distributions for both treated and non-treated groups around 0.15 to scores that are centered almost three times higher around 0.45. This can be interpreted as the covariates selected doing a much better job at capturing qualities of company performance and, hopefully, reduce the inherent selection bias evident within the study.

5.3 Analysis 1 Retest Results

Below are the results of the retested Analysis 1 after implementing the necessary changes described above. With the new changes, results are much more consistent than the first analysis in the sense that they, for the most part, trend in the same direction throughout the time horizon of the analysis. This, if anything, provides a serious benefit over the first attempted Analysis 1, which was showing statistically significant data in Year 5 for some growth variables.

5.3.1 Revenue Growth

	Revenue Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	0.122***	0.057**	0.100***
	(0.025)	(0.022)	(0.024)
PE	-0.020	-0.027	0.014
	(0.023)	(0.022)	(0.024)
Propensity Score	0.158***	0.182***	0.029
	(0.059)	(0.053)	(0.056)
Observations	829	762	658
R^2	0.010	0.017	0.001
Adjusted R^2	0.007	0.014	-0.002
Residual Std. Error	0.243 (df=826)	0.222 (df=759)	0.223 (df=655)
F Statistic	4.010** (df=2; 826)	6.546*** (df=2; 759)	0.298 (df=2; 655)
Test for PE Significance			
PE	-0.0199	-0.0267	0.0140
std err	0.023	0.022	0.024
t	-0.855	-1.217	0.584
P> |t|	0.393	0.224	0.559
0.025	-0.066	-0.070	-0.033
0.975	0.026	0.016	0.061

*p<0.1; **p<0.05; ***p<0.01

Table 6: Test for PE Significance with Revenue Growth %

	Net Income Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	0.009	-0.031*	-0.016
	(0.013)	(0.016)	(0.013)
PE	0.032**	-0.009	0.003
	(0.014)	(0.017)	(0.014)
Propensity Score	-0.035	0.072*	0.030
	(0.031)	(0.039)	(0.031)
Observations	711	666	561
R^2	0.009	0.006	0.002
Adjusted R^2	0.007	0.003	-0.002
Residual Std. Error	0.131 (df=708)	0.155 (df=663)	0.119 (df=558)
F Statistic	3.340** (df=2; 708)	1.911 (df=2; 663)	0.486 (df=2; 558)
Test for PE Significance			
PE	0.0323	-0.0095	0.0029
std err	0.014	0.017	0.014
t	2.356	-0.571	0.205
P> |t|	0.019	0.568	0.838
0.025	0.005	-0.042	-0.025
0.975	0.059	0.023	0.031

*p<0.1; **p<0.05; ***p<0.01

Table 7: Test for PE Significance with Net Income Growth %

	EBITDA Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	-0.025	0.020	0.042*
	(0.021)	(0.018)	(0.021)
PE	0.173***	0.034*	0.027
	(0.023)	(0.020)	(0.024)
Propensity Score	0.105**	0.111**	0.015
	(0.051)	(0.044)	(0.053)
Observations	791	707	627
R^2	0.073	0.013	0.002
Adjusted R^2	0.071	0.010	-0.001
Residual Std. Error	0.223 (df=788)	0.186 (df=704)	0.204 (df=624)
F Statistic	31.224*** (df=2; 788)	4.501** (df=2; 704)	0.654 (df=2; 624)
Test for PE Significance			
PE	0.1735***	0.0337	0.0267**
std err	0.023	0.020	0.024
t	7.611	1.648	1.106
P> |t|	0.000	0.100	0.269
0.025	0.129	-0.006	-0.021
0.975	0.218	0.074	0.074

*p<0.1; **p<0.05; ***p<0.01

Table 8: Test for PE Significance with EBITDA Growth %

	Liquidity Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	-0.048***	0.002	-0.034***
	(0.013)	(0.018)	(0.013)
PE	-0.001	0.011	-0.022
	(0.013)	(0.019)	(0.014)
Propensity Score	0.039	-0.018	0.020
	(0.030)	(0.042)	(0.032)
Observations	795	727	647
R^2	0.002	0.001	0.004
Adjusted R^2	-0.000	-0.002	0.001
Residual Std. Error	0.134 (df=792)	0.183 (df=724)	0.128 (df=644)
F Statistic	0.830 (df=2; 792)	0.258 (df=2; 724)	1.313 (df=2; 644)
Test for PE Significance			
PE	-0.0008	0.0111**	-0.0217
std err	0.013	0.019	0.014
t	-0.065	0.581	-1.505
P> |t|	0.949	0.561	0.133
0.025	-0.027	-0.026	-0.050
0.975	0.025	0.049	0.007

*p<0.1; **p<0.05; ***p<0.01

Table 9: Test for PE Significance with Liquidity Growth %

	ROE Growth %		
	(Year 1)	(Year 3)	(Year 5)
Intercept	0.006	0.015	-0.024
	(0.016)	(0.019)	(0.017)
PE	0.004	0.013	-0.010
	(0.018)	(0.020)	(0.019)
Propensity Score	0.032	-0.015	0.093**
	(0.040)	(0.045)	(0.041)
Observations	731	687	600
R^2	0.001	0.001	0.009
Adjusted R^2	-0.002	-0.002	0.006
Residual Std. Error	0.169 (df=728)	0.180 (df=684)	0.155 (df=597)
F Statistic	0.346 (df=2; 728)	0.260 (df=2; 684)	2.671* (df=2; 597)
Test for PE Significance			
PE	0.0038	0.0129	-0.0105
std err	0.018	0.020	0.019
t	0.216	0.647	-0.561
P> |t|	0.829	0.518	0.575
0.025	-0.031	-0.026	-0.047
0.975	0.038	0.052	0.026

*p<0.1; **p<0.05; ***p<0.01

Table 10: Test for PE Significance with ROE Growth %

5.3.2 Net Income Growth

5.3.3 EBITDA Growth

5.3.4 Liquidity Growth

5.3.5 ROE Growth

5.4 Analysis 2

Described below are the results of the event study analysis. In general, growth was analyzed to be sustained on average across all the growth metrics tested.

5.4.1 Revenue Growth

	T	dof	alternative	p-val	CI95%	cohen-d	BF10	power
T-test	-1.293271	57	two-sided	0.201134	[-1.18, 0.25]	0.169815	0.316	0.246207

Figure 4: Compiled Revenue T-test

As seen in Figure 14, revenue growth t-stats are centered around 0, which indicates that predictions for estimates were well-sustained after IPO. PortCos through the time period are able to maintain consistent growth as they were when the companies were private. Quite surprising in the histogram is the fact that there are relatively short tails in the graph, which could be potentially caused by the small amount of companies being tested. In theory, we'd expect the t-statistic histogram to be normally distributed as the amount of companies in the analysis increases.

To confirm the results, I run another t-test on top of the compiled results, and calculate a t-stat of -1.29, as seen in Figure 4. As is evident with a p-value of .20, the results are insignificant a 1,5, and 10% level, which leads us to conclude that the companies are able to maintain growth at a consistent rate in the long term.

5.4.2 Net Income Growth

	T	dof	alternative	p-val	CI95%	cohen-d	BF10	power
T-test	0.240009	54	two-sided	0.811232	[-0.74, 0.94]	0.032363	0.151	0.056392

Figure 5: Compiled Net Income T-test

Similarly, the net income growth histogram is centered around 0, which again indicates that growth rates were sustained on average with portcos after IPO.

When testing for significance of the compile t-stats to confirm what the histogram appears to be telling us, I again analyze the compiled t-stats with another t-test. In figure 5, we calculate a t-stat that is closer to 0 than before at 0.24. Unlike revenue growth, however, the 95% confidence interval is slightly more spread out between -0.74 and 0.94.This being the case, we fail to reject the H2 hypothesis that companies are able to maintain similar growth rates as they were during private equity control.

5.4.3 EBITDA Growth

	T	dof	alternative	p-val	CI95%	cohen-d	BF10	power
T-test	1.735049	57	two-sided	0.088137	[-0.14, 1.9]	0.227823	0.585	0.399814

Figure 6: Compiled EBITDA T-test

When analyzing EBITDA growth, we can see in Figure 16 that the histogram of t-stats is seemingly normally distributed. A closer look also shows that the peak of the histogram is slightly higher than 0. This could potentially mean that the actual growth data is statistically significant than that of what was projected by the model. The t-stat calculated on the model confirms this at 1.74 with a p-stat of 0.09. The model is statistically significant at the 10% level. On average, I conclude that EBITDA growth rates for the portfolio companies statistically differ from their EBITDA growth prior to IPO, and potentially outpace their growth once entering the public market. Given this, we fail to reject the H2 hypothesis.

5.4.4 Liquidity Growth

	T	dof	alternative	p-val	CI95%	cohen-d	BF10	power
T-test	0.76166	53	two-sided	0.449639	[-0.56, 1.24]	0.103649	0.195	0.116136

Figure 7: Compiled Liquidity T-test

The liquidity growth t-test histogram in Figure 17 again shows a seemingly normal distribution centered between 0-1. Unlike the EBITDA growth histogram, we would expect the data to be statistically insignificant despite a higher distribution center since the center appears to be offset by 1 and because of the normal distribution. The calculated t-stat of 0.76 and p-value of 0.44 further confirms intuition. The p-value is insignificant at 1,5, and 10% levels and thus conclude again that the growth metric is sustained on average post-IPO.

Given 1 and 5% significance levels, we would reject the H2 hypothesis and conclude that liquidity growth estimates would be statistically significant from pre-IPO data. Intuitively, this makes sense. Portfolio companies are often levered with debt during the investment period for private equity firms to maximize returns, which directly affects the liquidity of a company. It'd only be natural for these companies to increase liquidity at a faster rate when they have less interest to pay.

5.4.5 ROE Growth

	T	dof	alternative	p-val	CI95%	cohen-d	BF10	power
T-test	-0.340528	54	two-sided	0.73478	[-0.95, 0.67]	0.045917	0.156	0.062915

Figure 8: Compiled ROE T-test

Finally, we test significance of ROE growth. In Figure 18 we see a high-peaked relatively normal distribution around 0, which on first glimpse would indicate that there are no discernible differences between what the regression models predicted and actual ROE growth estimates on average.

Another t-test on the histogram confirms what is initially inferred. Over the five year period tested post IPO, there is no significant difference in the average growth rates for the companies tested and what was predicted from the model. A t-stat of -0.34 and p-value of 0.73 in sufficient for us to fail to reject the H2 hypothesis.

5.4.6 Discussion of Outliers

Within each of the distribution plots in Section 7.2, outliers are apparent. Although some are more obvious than others by simply looking at the graph, the visually low kurtosis of each of the graphs would indicate that there are non-obvious outliers in the models. For the sake of clarity, I define outliers in the models as t-statistics 1.5 Interquartile ranges (IQRs) over the 75th percentil and 1.5 IQRs below the 25th percentile.

	companies	significance
0	Forterra	-5.23
1	Summit Materials (Building Products)	7.777
2	The Habit Burger Grill	-12.297
3	K2M	-5.955
4	Envision Healthcare	4.806

(a) Outlier Revenue Growth

	companies	significance
0	Forterra	-4.943
1	Summit Materials (Building Products)	7.696
2	The Habit Burger Grill	-15.783
3	Sprouts Farmers Market	-4.884

(b) Outlier Net Income Growth

	companies	significance
0	Forterra	-5.16
1	Summit Materials (Building Products)	-8.754
2	The Habit Burger Grill	15.068
3	Smart & Final Holdings	-6.265
4	Pinnacle Foods	5.399
5	K2M	-4.649
6	Envision Healthcare	4.741

(a) Outlier Liquidity Growth

	companies	significance
0	Forterra	-4.992
1	Ply Gem Industries	-4.928
2	The Habit Burger Grill	-15.141
3	Smart & Final Holdings	7.61
4	Pinnacle Foods	4.487
5	Envision Healthcare	-5.163

(b) Outlier ROE Growth

	companies	significance
0	Forterra	4.93
1	Advanced Disposal	-4.819
2	Summit Materials (Building Products)	5.168
3	The Habit Burger Grill	-12.374
4	Floor & Decor	-4.23
5	Sprouts Farmers Market	-3.963
6	Pinnacle Foods	5.003
7	K2M	19.938
8	Envision Healthcare	7.223
9	Paycom Software	5.064
10	Quality Technology Services	5.445

Figure 11: Outlier EBITDA Growth

By the Dataframes above we can see that several of the companies are outliers across some or all growth metrics tested and are worthwhile to look into further to investigate the cause of the outlier data. The outlier companies include Forterra, Summit Materials, The Habit Burger Grill, K2M, Pinnacle Foods, Envision Healthcare, Sprouts Farmers Market, and Smart & Final. Data used for the companies is shown below at the time of IPO, one year after IPO, and five years post-IPO. Of the outliers, the two that most stand out are The Habit Burger and K2M. While K2M show very high statistical significance for EBITDA growth post IPO, The Habit Burger shows strong negative significance across the board with the exception of liquidity growth.

Gross Profit	Diluted EPS	Cash Dividends Paid	Debt to Equity	Stock Price	Price to Tangible Book Value
13000.248	-52.400000	-38729.000000	0.000000	948.80	6.740544
19244.000	-52.200000	-38729.000000	0.000000	732.80	10.396734
26896.000	10.400000	-103090.000000	0.301983	97.40	1.936659
34759.894	-14.643333	-108152.666667	0.422832	154.42	4.861357

Figure 12: The Habit Burger Estimation Window Regressors

Gross Profit	Diluted EPS	Cash Dividends Paid	Debt to Equity	Stock Price	Price to Tangible Book Value
46158.25	-8.900000	-38729.00	0.075000	198.59750	6.736352
56751.00	-20.815000	-38729.00	0.417950	107.87750	2.419347
62319.00	3.370000	-59739.75	1.277493	39.54500	2.534211
68005.00	-13.952500	-52892.00	1.042232	128.06250	3.239972
77567.75	-44.685243	-29046.75	0.407823	103.58372	1.982157

Figure 13: The Habit Burger Event Window Regressors

Gross Profit	Diluted EPS	Cash Dividends Paid	Debt to Equity	Stock Price	Price to Tangible Book Value
70021.0	-108.399790	-38729.00	0.000000	182.999085	4.104490
91183.0	-12.640000	-38729.00	0.350007	19.620000	2.866275
107422.0	-241.999550	-38729.00	0.100000	185.999070	1.620008
116874.0	-86.850398	-69680.75	0.525190	147.025436	17.681844

Figure 14: K2M Estimation Window Regressors

Gross Profit	Diluted EPS	Cash Dividends Paid	Debt to Equity	Stock Price	Price to Tangible Book Value
137448.0	-118.944392	-30094.5	0.156542	71.329715	4.817051
151083.0	-2.785000	-38729.0	0.569172	26.542500	6.893932
163360.0	-177.756963	-38729.0	0.386513	197.951622	2.711255
176749.0	-7.620000	-26610.0	0.824683	38.453480	2.901603

Figure 15: K2M Event Window Regressors

Above we see both the estimation and event window regressors for The Habit Grill and K2M. Two things of similarities in both of them are the redundant variables in the `Cash Dividends Paid` column and some missing values for both in the `Debt to Equity` column of their respective estimation windows. These redundant variables were the result of populating null values with column medians. As noted, the regressors were chosen specifically because the columns are some of the most populated that were given in the original financial dataset, and are common indicators when assessing the financial health of a company. With this in mind, some null entries were still present in the columns selected, and have introduced bias in the model. Upon removing these two columns for The Habit and K2M in particular, both companies saw substantially reduced t-statistics, which would indicate that the models were doing a better job of estimating growth metrics.

6 Conclusion

This analysis provides evidence that private equity involvement has had an impact on growth rates of portfolio companies that IPO'd from the beginning of 2010 to the beginning of 2018. When compared to the 953 non-PE-backed companies that IPO'd within the same time frame, the 141 analyzed portfolio companies showed insignificant differences in growth measures of revenue and net income, but do display highly significant differences in EBITDA and liquidity growth. Notably, portfolio companies are seen to have significantly lower levels of liquidity growth three years after private equity divestment and significantly higher levels of EBITDA growth at years one and five after exit. EBITDA growth was tested to be significantly higher at years one and three with growths rates on average being 53% and

38% additional percentage points higher than non-treated companies. Liquidity, on the other hand, is recorded to be 160% less additionally in mean growth of portfolio companies.

In addition to this, the analysis provides further evidence that companies are able to sustain, and potentially increase their financial health once private equity firms divest. The 54 portfolio companies tested showed no significant differences in net income, revenue, EBITDA, and ROE growth following the IPO, and on average experienced higher liquidity growth than during the investment period. This suggests that not only are these companies well-positioned to succeed on average with PE investment,

Although my analysis does not dive into the root cause for this difference in estimates, I suggest that it is due to the business model of private equity to leverage as much debt as possible to acquire these portfolio companies. This is partially controlled since I include total debt as a covariate to my propensity score regression, but missing company data around this parameter implies that I cannot infer any causality from it. Though the evidence I present cannot infer conclusively if portfolio companies end up *better off* than their non-backed counterparts, I do find significant differences in growth measures in support of the initial hypothesis.

7 Appendix

7.1 Analysis 1 Growth Distributions

This section displays violin plots of all tested measures of growth and demonstrates the differences in distributions of data between portolio and non-treated companies.

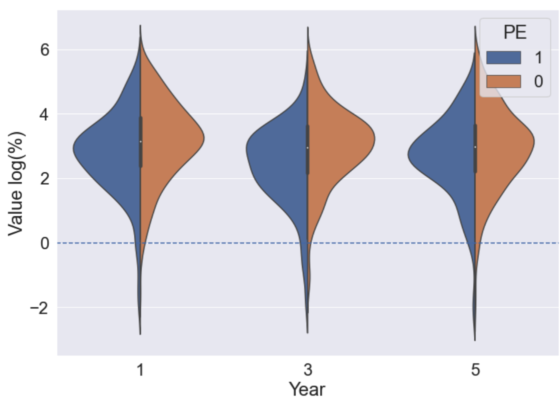

Figure 16: Log Growth Rate (%) of Revenue

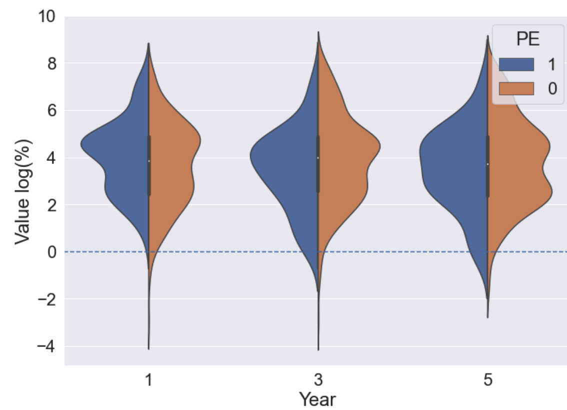

Figure 17: Log Growth Rate (%) of Net Income

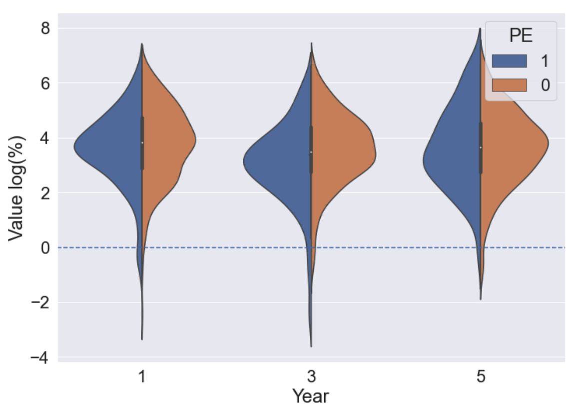

Figure 18: Log Growth Rate (%) of EBITDA

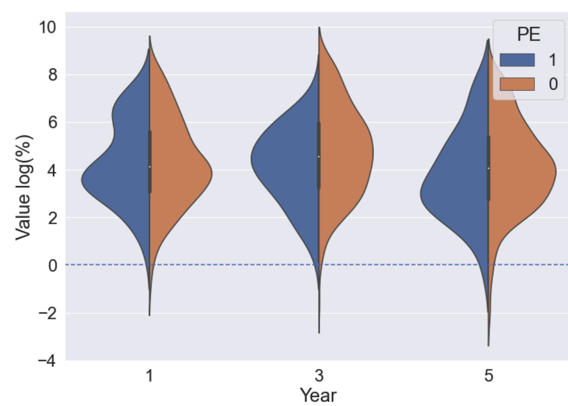

Figure 19: Log Growth Rate (%) of Liquidity

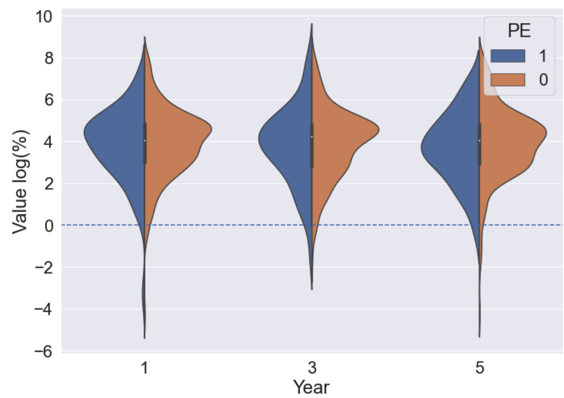

Figure 20: Log Growth Rate (%) of ROE

7.2 Analysis 2 Significance Distributions

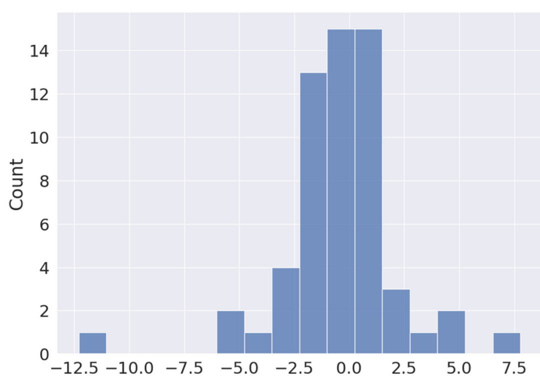

Figure 21: Revenue Growth T-Statistic Plot

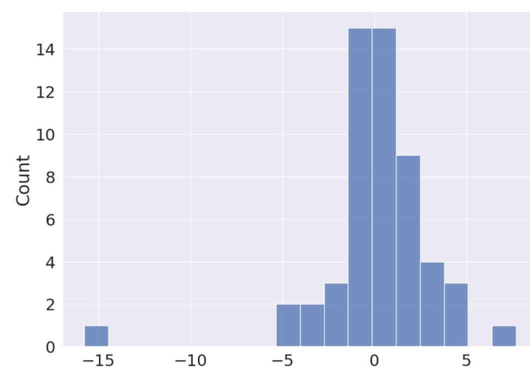

Figure 22: Net Income Growth T-Statistic Plot

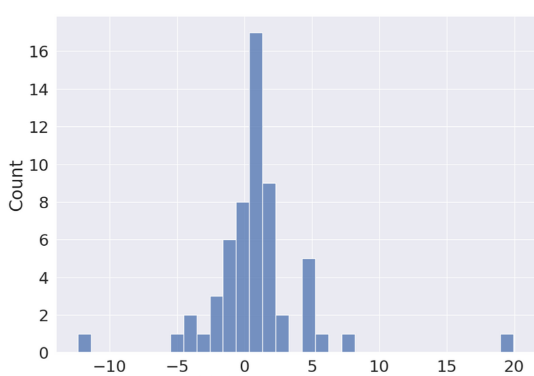

Figure 23: EBITDA Growth T-Statistic Plot

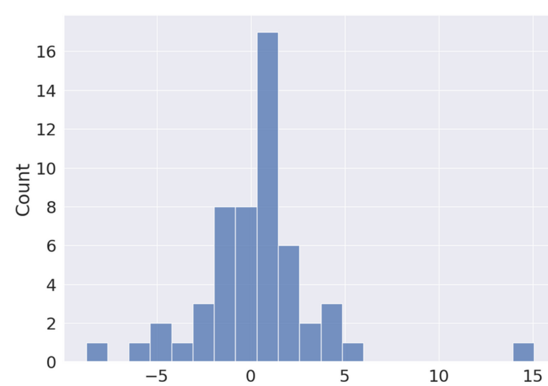

Figure 24: Liquidity Growth T-Statistic Plot

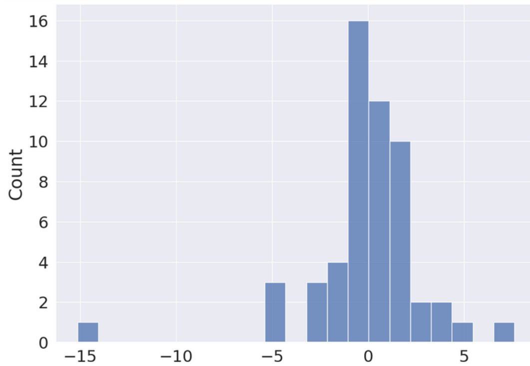

Figure 25: ROE Growth T-Statistic Plot

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