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**Title thesis**: Non-linear combinations of multiples to estimate equity value
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**Abstract:** This paper examines the valuation performance of non-linear combinations of simple multiple valuation outcomes. Logarithmic transformations of the valuation outcomes based on revenue and cash flow multiples provide the same accuracy as the linear combination- or simple valuations model. However, when considering only recent IPOs as comparable firms, the valuation errors significantly drop for the combined models. As the popularity of multiple valuation stems from its simplicity, one could ask to what extent it is preferable to expand and complicate this model.

# Contents

# 1 Introduction

The term initial public offering *(IPO)* has been around for a long time, describing a private firms' decision to offer new shares to the public in a stock issuance. There are various reasons for a firm to make this decision, such as raising new capital or rewarding prior investors. The firms conducting these IPOs are usually relatively young and therefore there is not a lot of financial information available about them. Another presumption is that firms conducting IPOs have valuable growth opportunities which are hard to capture in the expected future cash flows. This makes their valuation process a difficult task, something that has been widely discussed in prior research the past decades.

In corporate valuation the emphasis is often put on the use of the discounted cash flow theory. In various cases such as with IPOs, however, the uncertainty of future cash flows and limited information available asks for a different approach. Popular among practitioners for its simplicity is the use of multiples as a supplement to DCF analysis or on its own. This simplicity stems from the fact that not a lot of information is needed, while the valuation is based on the same fundamentals of the other approaches; value increases in future business opportunities and decreases in risk (Liu, Nissim, & Thomas, 2002). The basis of multiple valuation consists of finding firms with a comparable degree of size, growth and risk. By calculating certain performance measures for these benchmark firms and applying them to the firm of interest, one can derive its value. It is based on the idea that similar assets sell at similar prices. There is wide literature on various aspects regarding this topic, however, few studies apply their findings to the process of IPO valuation. Those that do, often focus on just a small part of all of the aspects associated with multiple valuation.

The traditional process of multiple valuation consists of converting one specific value driver to a multiple. Afterwards, the average of the calculated multiples of comparable firms is used to estimate the equity value of the valued firm. This process is repeated for several multiples in order for the valuation practitioner to gain insight in the possible value of a firm. As illustrated by (Yoo, 2006), a combination of these outcomes may be a very feasible way of valuing a firm more accurately. He assumes that the relationship between the equity value and these single valuation outcomes is linear, while this may not be the case. Valuation outcomes provided by certain multiples may be systematically higher or lower than the actual values are. The mispricing could hold for the entire range of variables or be more prevalent in certain intervals, such as between two price levels. All in all, there is no confirmation of this assumed linear relation.

This study aims to find a non-linear combination of outcomes that increase the valuation accuracy of multiples even further. By running an out-of-sample regression of valuation outcomes on equity value for a large number of firms, the weights of the single valuations will be determined. To broaden the focus of this study to most aspects of multiple valuation, different types of models and groups of comparable firms are considered in the analyses.

The remainder of the paper is organized as follows; Section 2 reviews previous literature on the subject. Section 3 sets a framework for the study and the analyses. Section 4 presents the data. Section 5 presents the results of all performed analyses. Section 6 provides the conclusion of the study as well as its limitations.

## 2 Related Literature

The past few decades there has been a large amount of literature on the topic of multiple valuation. These studies often focus only on certain aspects of the topic and under quite strict conditions, such as a limited number of firms-years, a subset of multiples or the selection of comparable firms. Out of these studies, relatively few apply their findings to the process of IPO valuation. The discounted cash flow method (*DCF*), on the other hand, has gained significantly more attention from academia despite the frequent use of multiple analysis. While the DCF method is much more complicated and thus has a far more extensive theoretical background, a proper analysis of the foundation of multiple valuation may significantly improve its accuracy.

### 2.1 Alternative valuation frameworks

While multiple valuation is particularly popular for its simplicity, there are quite a few other methods used to value businesses. One of these methods is the DCF, which involves estimating cash flows generated by a firm and discounting them for their firm-specific risk. In business valuation it is the most widely used technique and has been for some time. Based on a firm theoretical foundation, the DCF method has a lot more input factors to consider than multiple valuation does. This makes the method able to refine the valuations specific to the firm of interest in order to improve accuracy.

However, despite its large use, DCF is often abandoned in favor of the multiple valuation due to the fact that cash flows and discount rates can be hard to estimate. The multiple method works best when a similar group of firms is available that can be used to compare with. While this method may reduce the probability of mis valuing relative to other approaches, a well-known caveat is that it does not protect against entire industries or sectors being wrongly valued. (Kaplan & Ruback, 1995) compare the results of DCF and multiple valuation of leveraged transactions based on cash flow multiples. They find similar results under both methods although it appears that the DCF produces slightly better estimates. Other approaches such as the cost-based or asset-based approach both have their advantages. However, often due to uncertainty of information, assets or future cash flows, these methods are of relatively little use when valuing IPOs.

### 2.2 Fundamental factors and statistical measures

Prior studies have put their emphasis on commonly used multiples such as the price-to-earnings (P/E) ratio, enterprise value-to-EBITDA (EV/EBITDA) and others. (Kim &

Ritter, 1999), among others, state that the use of industry specific ratios may improve valuation accuracy. Furthermore, they add forecasted earnings to the list of conventional value drivers and find a significant difference in valuation accuracy. (Liu et al., 2002) show that, contrary to the popular view, their findings have an established multiple ranking order for all industries.

(Beatty, Riffe, & Thompson, 1999) examine linear combinations of multiples as opposed to the simple multiple valuations that had been done before. Their findings provide evidence that valuation errors are proportional to value and they introduce the price-scaled regressions that we still use today. Not everyone agrees with the view that the relationship between a multiple and its value driver should be linear. (Herrmann & Richter, 2003) are amongst those people and explore whether non-linear relations between multiples and fundamental control factors exist. They find that their non-linear models provide lower valuation errors in comparison to the linear counterparts.

(Yoo, 2006) examines a different approach by combining several simple multiple valuations in order to improve its accuracy. He finds that a weighted combination of several simple multiple valuations may improve valuation accuracy compared to multiple valuation using a single historical multiple. A caveat of his study is that only linear combinations of outcomes are considered. As far as I am concerned, there are very few studies that explore this non-linear combination of outcomes to improve valuation accuracy. This study will attempt to reduce the valuation accuracy errors in valuing IPOs by combining both works of (Kim & Ritter, 1999) and (Yoo, 2006). The main hypothesis that will be examined is: *The use of a non-linear combination of multiples yields the same valuation accuracy as a linear combination of multiples.*

A largely unexplored aspect of multiple valuation is the summarizing of the comparable firms' multiples. Most studies assume the median of multiples is the best estimator as it accounts for skewness and eliminates the influence of outliers. (Baker & Ruback, 1999) challenge this view and find that the harmonic mean dominates all other estimators. (Liu et al., 2002) find that this result also holds for them and that the harmonic mean is an unbiased estimator of the valued firms' multiples.

Research has shown that there are more factors than just these financial variables that drive equity value. For example, (Schultz & Zaman, 2001) and (Van Der Goot, n.d.) have shown that greater relative ownership retained by pre-issue shareholders should be a positive signal to investors as the issue is not just a means for the pre-issue shareholders to cash out on a losing team. This is consistent with the signaling theory. Also, (Shleifer & Vishny, 1997) point out in their study that greater insider ownership may reduce agency costs as the interests of managers and shareholders are better aligned. According to this theory, greater relative ownership would result in a higher stock price, keeping other factors constant.

## 2.3 Comparable firms

Common practice in the valuation of IPOs is to measure its operational and financial performance with that of publicly owned firms in similar industries. The firm and its underwriters will set an offer price according to the market ratios for these similar firms after adjusting them for firm-specific differences. The idea behind the comparable firm analysis is that equal firms, whether it be based on revenue, growth, industry or something else, will sell at equal prices. This would make a 'comparable firm' a good substitute for the firm of interest and analyses based on this comparable firm its financials should provide results that are accurate for the firm of interest. There have been a lot of studies researching the effect of the chosen group of comparable firms on the accuracy of valuation.

(Alford, 1992) points out in his study that, keeping only the P/E multiple in mind, choosing a group based on industry alone or in combination with return on equity ($ROE$) or total assets leads to the most accurate valuations. This improves by increasing the number of standard industry classification ($SIC$) digits, which he uses to define an industry. Other studies, such as (Yoo, 2006) and (Kim & Ritter, 1999), use a more hand-picked approach in their selection. (Herrmann & Richter, 2003) look at the effect on valuation accuracy when using performance-controlled multiples, that is, making a selection of comparable assets based on control factors.

To test whether these findings also hold in this study, I will explore whether valuation accuracy increases when choosing comparable firms on the basis of industry classification instead out of the cross section: *The selection of comparable firms on basis of industry classification provides better valuation accuracy.*

As shown in past literature, IPO issuance is known for its cyclical behavior. 'Hot issue IPO markets' imply a relatively large number of IPOs in comparison to the average. (Chemmanur & He, 2011) provided a study on this cyclicality and showed that firms 'time' their IPOs in hot issue periods as this invasion of IPOs lead to a collective optimism among investors. Also, market sentiment might have different effects on conducted IPOs and thus on the performance of multiples. In order to see whether there are systematical differences in the multiple performance when using recent IPOs or IPOs in general as a set of comparable firms, I test the following hypothesis: *The use of recent IPOs as a group of comparable firms as opposed to IPOs in general has no effect on the valuation accuracy of multiples.*

## 2.4 Firm Age

IPOs are presumably often conducted by firms with valuable growth opportunities for which it is hard to incorporate growth into future value. This difficulty would be most severe for young growth firms (Kim & Ritter, 1999). Because of this, older firms with more established financial information should be valued more accurately. The emphasis from an investors point of view tends to be more on the profitability of the firm instead of growth rate. For younger firms this holds vice versa. Another observed characteristic is that there seems to be a significant correlation between the firm age and the post IPO excess returns (Clark, 2002). To test for differences of certain aspects among both groups, I will split the IPOs into young and old firms and test the following hypothesis: *The valuation accuracy of multiples is larger for older firms than for younger firms.*

# 3 Methodology

## 3.1 Value drivers

In order to compare results in this study to those of others, a similar methodological framework needs to be used. As this study partially builds on the composite approach applied in (Yoo, 2006) as well as the relevance to IPOs from (Kim & Ritter, 1999) work, aspects from both works will be applied to this study.

Since the entire idea of initial public offering is transferring capital and shares to respectively the firm and the investor, I will focus this study on the market value of a firm its equity. This is calculated using either the market capitalization or the share price. In this study I will use the share price as measure of equity value, more specifically will I try to most accurately estimate the stock its first-day market closing price. In order to do this, I must examine the underlying factors that drive the stock price, so called value drivers. The study will look at the ability of these value drivers to estimate equity value on a standalone basis as well as a combination of them.

As prior research has shown to be most important for equity valuation, the following financial value drivers are selected: earnings, revenues, cash flows and book value of equity. These are defined as follows:

- **Earnings per share (EPS)** – earnings per share for the twelve-month period prior to the offering.
- **Revenues (REV)** – total revenues for the latest twelve-month period prior to the offering.
- **Cash flows (EBITDA)** – earnings before interest, taxes, depreciation and amortization for the twelve-month period prior to the offering.
- **Book value of equity (BPS)** – common equity (book value) after offering divided by shares outstanding after offer.

As suggested by (Yoo, 2006); "Earnings before interest, taxes, depreciation and amortization (*EBITDA*) may be the best available proxy for the future cash flows that underlie equity values". The EBITDA is the only cash-flow value driver I consider in this study because cash flows do not necessarily reflect value creation. The purchases or sales of certain assets or liabilities have an effect on the cash flows but do not per se create or diminish value for a firm. In general, the use of cash flow multiples seems to be justified by the fact that they appear to be less susceptible to manipulation by management. Book value and earnings are accounting numbers that have been widely used to calculate multiples. Analyses performed with multiples based on these numbers often outperform any of the other multiples, as they are assumed to represent a firm its "fundamentals". As all of the valuation multiples carry some incremental information in them that is not captured by other multiples, combining the outcomes of these multiples may be a good way to enhance accuracy.

Not just financial variables are able to drive a firm its price, there are a lot more direct or indirect influences. To test whether there is an effect of the amount shares retained at IPO on price, the non-financial variable equity retained ($EQRET$) is introduced, which indicates the percentage of shares not issued in the IPO relative to the total number of shares outstanding after the offer.

### 3.2 Simple multiple valuation

First, I want to examine the ability of the value drivers to predict the stock price for the valued firm. The standard way of converting value drivers into equity value is by capitalizing the calculated multiple from the benchmark group of firms. These so called simple multiple valuations ($SMV$) will form the basis for the model that explores combinations of these outcomes:

$$\widehat{EV_i} = (\frac{P}{X})_{C,i} * X_i \tag{1}$$

Where $\widehat{EV_i}$ is the estimated equity value of firm $i$, $(P/X)_{C,i}$ is the averaged stock price ($P$) divided by the value driver ($X$) of the comparable firms for firm $i$ and $X_i$ is the corresponding value driver for firm $i$. This is consistent with the simple multiple valuation procedure used in (Yoo, 2006).

### 3.3 Combined approach of multiples

#### 3.3.1 Linear combination of multiples

After the single multiple valuations have been performed, they will be assigned weights based on their ability to predict equity value. A multiplication of these weights with their corresponding simple multiple valuation outcome will give the equity value of the firm of interest. In the first stage of this analysis a linear combination of multiples is assumed. The weights will be determined by performing an out-of-sample regression with the following formula:

$$P_i = \sum_{k=1}^{m} \beta_{ki} * EV_{ki} + \epsilon_i \tag{2}$$

$$1 = \sum_{k=1}^{m} \beta_{ki} * \frac{EV_{ki}}{P_i} + \frac{\epsilon_i}{P_i} \tag{3}$$

Where $P_i$ is the stock price of firm $i$, $\beta_{ki}$ is the derived weight of the simple multiple valuation based on the $k$th value driver for firm $i$, $EV_{ki}$ is the estimated equity value for firm $i$ based on the $k$th value driver and $\varepsilon_i$ is the error term.

(Baker & Ruback, 1999), among others, show in their research that the residual as shown in the equation ($\epsilon_i$) is quite proportional to the price. This thought seems to be valid as my sample has a large range between the smallest and greatest observed values for some variables. Whether it be the estimated regression line or the averaged comparable firms' multiples in the simple multiple valuation, the goal is to summarize the data of many observations into a few parameters. When these parameters are applied to observations on the tails of the distribution, a distribution of prices for example, the length between the estimated and actual value will be far greater than for those observations in the center of the distribution. As my dataset does not have any negative values for price and thus the outliers will mostly be on the right-hand side of the distribution, it seems very likely that in my dataset the error term proportionally increases with price as well. While this heteroscedasticity does not cause bias in the regression coefficient estimates, it does make them less precise. By dividing equation (2) by price, the price-deflated residual will be homoscedastic and the estimated $\beta$ is likely to be more precise.

An out-of-sample procedure implies that part of the sample is withheld from the model identification and estimation process, in this case; the regression. The valued firm is removed from the group of comparables and the regression is performed on the training sample, which consists of (recent) comparable firms in either the same industry or the cross-section. Then, the estimated regression parameters are applied to the independent variables of the held-out observation; the valued firm. In order to see whether the model generalizes well and is applicable to firms outside of the training sample, the accuracy of the estimated equity value is examined by looking at the valuation error, which will be discussed in section 3,6.

In the formulas mentioned above, I have assumed that the value driver is the only variable that affects the price. In practice this is not the case, there are a lot more variables that have an influence on the price. Also, if the relationship between the price and the value driver is non-linear, the higher powers of the value driver are not taken into account in either formula (2) or (3). As I do not expect the average effect of these omitted factors to equal zero, I will allow for an intercept in order to increase prediction accuracy:

$$P_i = \alpha + \sum_{k=1}^{m} \beta_{ki} * EV_{ki} + \epsilon_i \tag{4}$$

$$1 = \frac{\alpha}{P_i} + \sum_{k=1}^{m} \beta_{ki} * \frac{EV_{ki}}{P_i} + \frac{\epsilon_i}{P_i} \tag{5}$$

As explained above, dividing formula (4) by price will most likely yield more precise estimates.

### 3.3.2 Non-linear combination

The main hypothesis of this study is whether the use of a non-linear combination of multiples yields the same valuation accuracy as the linear combination does. Therefore, some log-transformed variations of the regression above will be performed as well. It is quite surprising why often only a linear regression is considered as some academics, such as (Damodaran, 2006), state that the relationship between a multiple and its value driver is not linear. One reason for this may be that the popularity of the multiple valuation comes, for at least some part, from its simplicity. Non-linear regression makes the method more difficult to understand and justify. (Herrmann & Richter, 2003) explore in their research a possible non-linear relationship between multiples and their corresponding fundamentals. They find that this method of controlling for fundamentals does not necessary result in the highest prediction accuracy compared to their other methods used. (Yoo, 2006) completed his research and paved the way for my paper. This paper will continue his research in considering non-linear methods to derive the simple multiple valuation outcome weights.

The data for revenue and EBITDA is reasonably more skewed than the data for book value and earnings when looking at the descriptive statistics in table 2. Their standard deviation is almost double their mean, which also holds for the multiples they are based upon. This makes it highly likely that the simple valuation outcomes based on these multiples is skewed as well. In order to allow for proper analyses and see whether other variations of the regressions above perform more accurate, some log transformations to the regressions have been made. By taking the log of the values, I transform the distribution of the values to a more normally shaped bell curve and aim to produce the smallest error possible when making a prediction. The data for the first-day closing price is a little skewed, so its logarithmic transformation will also be considered. The following transformations will be considered:

- **Linear-Log model (a)**

$$P_{c,i} = \alpha_i + \sum_{k=1}^{m} \beta_{ki} * ln(EV_{c,ki}) + \epsilon_{c,i}$$

- **Log-linear model (b)**

$$ln(P_{c,i}) = \alpha_i + \sum_{k=1}^{m} \beta_{ki} * EV_{c,ki} + \epsilon_{c,i}$$

- **Log-Log model (c)**

$$ln(P_{c,i}) = \alpha_i + \sum_{k=1}^{m} \beta_{ki} * ln(EV_{c,ki}) + \epsilon_{c,i}$$

As a result of the transformations, the obtained beta or weight has a different interpretation. For model a, an increase in the independent variable of one percent equals an increase in the dependent variable of 0.01 * $\beta$. For model b, an increase in the independent variable of one equals an increase in the dependent variable of (100 * $\beta$) percent. For the final model, an increase in the independent variable of one percent equals an increase in the dependent variable of $\beta$ percent.

### 3.4 Selection of peer firms

All analyses will be performed on both the full sample and the sample based on comparable firms. Prior literature on the topic of equity valuation has almost always put its focus on how comparable firms should be identified.

(Alford, 1992) finds that, using the stock price to historical earnings multiple, valuation errors of simple multiple valuation decline when industry is defined on the basis of two- or three-digit SIC codes as opposed to one. (Kim & Ritter, 1999) test these findings on their sample. To compare, they also perform their analyses on a sample with comparable firms that are hand-picked by a boutique firm that specializes in IPO research. Based on their results, they conclude that SIC codes frequently misclassify firms. A similar method of selection is by IBES classification, this is based loosely on SIC codes but is also subject to detailed adjustments. The more similar a certain firm is to the valued firm, the better its valuation accuracy will be. So, why not use a method that statistically selects firms on certain control factors such as size, risk, growth or even country. This is what the nearest neighbor algorithm can do.

The dispersion in methods used throughout literature shows that there is not a universally acknowledged ranking order and that the method of selection is conditional to the sample. Investment bankers, underwriters or analysts may sometimes, based on the IPO to be conducted, choose comparable firms with high or low multiples to justify a certain price. An advantage of selecting comparable firms by means of an algorithm or predefined category, such as SIC code or nearest neighbor method, is that the selection is not influenced by such an attempt to justify a certain multiple. On the other hand, use of these methods results in being subject to the arbitrariness of the classifications and may ignore many decent comparables.

The goal of this paper is to assess the differences in valuation accuracy under certain models with similar prior studies, specifically those of (Kim & Ritter, 1999) and (Yoo, 2006). As they respectively base their study on the SIC codes and IBES classification, which is loosely based upon SIC codes, I have chosen to make use of the SIC codes as industry identifiers. By doing so I attempt to minimize the difference in theoretical framework between the studies.

(Alford, 1992) points out in his study that valuation errors decline when the group of comparable firms is picked based upon SIC codes with two or three digits as compared to one digit, but that the use of four digits does not additionally improve the accuracy. Furthermore, out of the 4406 IPOs in the final sample, there are quite some industries that lack a sufficient number of four-digit SIC comparable firms. Because of this, I will classify by industry on the basis of three-digit SIC codes. In order to analyze the hypothesis regarding the group of recent comparable firms, that is, IPOs that went public in the two years prior to the valued firm, a minimum of four comparable firms per industry is necessary.

### 3.5 Selection of statistical measure of comparable multiples

In order to derive the average multiple for the comparable firms from all single multiples, a proper statistical measure should be used. In past studies the use of an arithmetic mean is quite common, however, researchers often take this method as a given and so the decision lacks theoretical backing. The most appropriate method should be based on the distribution of the multiples in the sample. (Lie & Lie, 2002) for example, make use of the median of observations as the comparable multiple to mitigate the effect of outliers. (Liu et al., 2002) find that the use of a harmonic mean of the comparable firms' multiples is an unbiased estimator of the valued firm its multiples. Because of this wide dispersion in methods used, several tests will be performed to see which measure yields the lowest prediction errors. The following measures will be tested:

- **Arithmetic mean**
- **Harmonic mean**
- **Ln-mean**
- **Median**

### 3.6 Measures of fit

The goal of this study is to assess the valuation accuracy of the non-linear combination of multiples as opposed to the linear combination. To do this, a measure of fit that allows for comparison between the different models is necessary. The importance of the chosen measure is also emphasized when comparing this study to those that have been done before. As most of the previous literature all follow similar measures of fit, I will also make use of these. The valuation accuracy will be measured across multiples and industries by *valuation error*, which is scaled by stock price and defined as follows:

$$VE_{ki} = \frac{P_i - P_{est,ki}}{P_i} \tag{6}$$

Where $VE_{ki}$ is the valuation error of firm $i$ based on the $k$th value driver, $P_{est,ki}$ is de estimated equity value of firm $i$ based on the $k$th value driver and $P_i$ is the observed price of firm $i$. In order to compare the results of this study to those of (Yoo, 2006), (Kim & Ritter, 1999), (Liu et al., 2002) and others, I will measure the size and distribution of valuation errors by the following means:

- **Mean of the absolute valuation errors (*MAVE*)**
- **Percentage of sample in which the absolute valuation error is within 15% of the price (*15% AVE*)**
- **Interquartile range of valuation errors (*IQVE*)**
- **Mean of the absolute valuation errors (*MEAN*)**

These statistics allow me to measure the valuation errors between multiples, industries and different models. It also shows me what the distribution of errors in my sample is. In order to reduce the skewedness of this error distribution, I will also measure the valuation error by taking the log of the ratio in formula (6). When examining the accuracy of the linear combination of multiples, the R-squared will be compared across different industries as well. This only works for the linear regressions as the underlying assumptions of the R-squared do not hold otherwise. Finally, I will provide certain visual representations of the distribution of the above-mentioned statistics for different multiples.

In order to compare the AVE between models, I will perform several Diebold-Mariano tests. This test compares the predictive accuracy of two forecasts on basis of either squared-error loss or absolute error loss. It defines the loss differential between two forecasts as the difference in valuation error of the two models and say the models have equal accuracy if the loss differential has zero expectation for all observations. The key assumption for using the Diebold-Mariano test is that the loss differential series $d_i$ is stationary. The Diebold-Mariano test utilizes the following test statistic:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T}}}$$

Where $\bar{d}$ is the sample mean of the loss differential, $\hat{f}_d(0)$ is a consistent estimate of $f_d(0)$ and T is the number of observations. Under the null hypothesis of no difference between models, the test statistic follows a standard normal distribution, DM $\sim$ N(0,1). There is a significant difference between the forecasts if the absolute value of the test statistic is larger than the two-tailed critical value for the standard normal distribution.

# 4 Data

## 4.1 Sample

The sample covers the past two decades ranging from January 2000 to December 2019. The initial sample consists of 39298 firms that underwent an issue in this period. The data used is merged from two sources: the ThomsonOne and Zephyr database. Firms are included in the sample if the IPO date, final offer price and first-day closing price are known. (Mikkelson & Partch, 1986) discussed differences in information between pure and mixed issues in their study. As mixed issues consist of multiple securities but are subject to one offer price as a whole, one cannot make a distinction in price for the separate securities. In order to achieve a more homogeneous sample and allow for proper comparison, I have excluded certain types of issuances such as unit offers, best effort offerings and reverse LBOs.

In order to perform the statistical tests necessary, all observations with missing values for *EPS*, *REV*, *BPS* & *EBITDA* have been removed from the sample. Furthermore, all firms with negative financial information have been removed from the sample as these numbers lead to negative valuation outcomes. In the final step of sample selection, a larger number of firms is excluded. There is no clear reason for this. One may be that a lot of firms have a missing value for just one of the value drivers. However, after clearing the sample of all those observations, relatively few remain. The final sample consists of 4406 firms. Table 1 summarizes the sample selection process.

| **Sample selection process** | **N** |
|---|---|
| IPOs between 2000-2019, drawn from SDC | 39298 |
| Exclusion of unit offers, best efforings & reverse LBOs | 4011 |
| Remaining | 35287 |
| Exclusion of firms with missing data for IPO date, final offer price & first-day closing price | 877 |
| Remaining | 34410 |
| Exclusion of firms with missing or negative data for EPS, REV, BPS & EBITDA | 30004 |
| Final Sample | 4406 |

Table 1: Sample selection process

### 4.2 Descriptive statistics

Table 2 summarizes the descriptive statistics of the variables and multiple ratios in the dataset. Before presenting the table some eliminations on the dataset have been made. Some IPOs with either suspicious data for certain variables or reliable data that did not fit the distribution have been eliminated. This amounted to outliers in the bottom and top two percent of observations. An example of one of these outliers is the IPO of the *Saudi Aramco* in end 2019, which was recorded as the largest IPO in history with proceeds of over 25 billion dollars and revenues in the pre-issue year of over 300 billons.

The mean of the P/E multiple equals 24.73 while the median is quite lower with a value of 18.95. This indicates that the distribution of the multiple is reasonably skewed to the right, which is confirmed by the large standard deviation. This holds for all multiples, and so for almost all value drivers, which indicates that still a number of large outliers are included in the dataset. In order to achieve a more homogenous dataset, all P/E multiples over 100 have been constrained to equal 100 and all M.B. multiples over 50 have been constrained to 50. This is common practice in a quite a few studies on the topic, for example in the work of (Kim & Ritter, 1999).

| Variable | Mean | Percentiles | | | Standard deviation |
|---|---|---|---|---|---|
| | | 25% | 50% | 75% | |
| Offer price (OP) | 3.43 | 0.57 | 1.54 | 6.24 | 3.11 |
| First-day closing price (P) | 4.68 | 0.74 | 2.02 | 7.74 | 3.73 |
| Book value per share | 1.75 | 0.42 | 0.99 | 3.55 | 1.19 |
| Earnings per share | 0.21 | 0.03 | 0.09 | 0.35 | 0.28 |
| Revenues | 254.80 | 34.40 | 79.90 | 206.05 | 543.10 |
| EBITDA | 54.96 | 7.20 | 16.60 | 43.35 | 119.54 |
| Equity retained | 0.75 | 0.75 | 0.75 | 0.85 | 0.18 |
| Proceeds | 118.76 | 12.83 | 45.32 | 120.54 | 236.55 |
| *P/E (P/EPS)* | 24.73 | 10.67 | 18.95 | 29.90 | 15.54 |
| *M/B (P/BPS)* | 2.32 | 1.12 | 1.97 | 3.21 | 1.99 |
| *P/REV* | 0.07 | 0.01 | 0.02 | 0.09 | 0.21 |
| *P/EBITDA* | 0.12 | 0.03 | 0.12 | 0.45 | 0.89 |

Table 2: Descriptive Statistics

# 5 Results

I begin by choosing a proper statistical measure of the comparable firms' multiples. This will be done by comparing valuation errors of the models under these different measures. In order to examine whether the differences in pricing error between these and the following models are of significant magnitude, the absolute valuation error ($AVE$) of the models will be compared by means of an ANOVA, Kruskal-Wallis or Diebold-Mariano test.

The analysis of variance ($ANOVA$) test is a statistical test which is used to compare means from independent groups using the F-distribution. The null hypothesis in this case is that the means of the absolute valuation errors are equal, a significant produced result indicates that there is a difference in means. The ANOVA tests has certain assumptions that need to be met, such as a normal distribution of data in the sample and random sampled observations. When this is not the case, a Kruskal-Wallis test will be performed. This test is the non-parametric version of the ANOVA and has relaxed assumptions. To test the direction of significant differences, a t-test or Diebold-Mariano test is used.

Throughout the paper I will maintain a significance level or alpha of five percent as the data suggests no reason to deviate from this number. Because of the large number of analyses and output results, only essential results will be tabulated in the paper. Other analyses and secondary research will either be in the appendices or left out because of its insignificance.

### 5.1 Simple multiple valuation

Table 3 presents the valuation errors of the multiples under the four different models. A quick look at the data gives the impression that the use of the harmonic mean of the comparable firms' multiples produces the lowest absolute valuation error. The mean of the valuation errors is closest to zero out of all groups, which suggests that this way of averaging the multiples gives a least biased estimate of the valued firms' multiple. An ANOVA and t-test confirm this presumption and shows that the harmonic mean significantly produces the lowest MAVE.

No difference is found between the use of either the median or the natural logarithm of the mean. However, both measures produce significantly better results than the arithmetic mean. This is consistent with the findings of (Liu et al., 2002) and (Beatty et al., 1999). The results produced under the arithmetic mean are by far the worst out of the four models. A reason for this might be that the way the arithmetic mean averages numbers is not the most suitable for this dataset as a lot of the numbers it is made up of are rates.

Following these results, in the remainder of this study I will compare models with the simple multiple valuations which use the harmonic mean as the comparable firms' multiple. Table 4 presents the correlations between the simple multiple valuation outcomes based on the harmonic mean. Above the diagonal is the Spearman correlation, below the diagonal is the Pearson correlation.

| Median | MAVE | 15%AVE | IQVE | MEAN | Harmonic Mean | MAVE | 15%AVE | IQVE | MEAN |
|---|---|---|---|---|---|---|---|---|---|
| VE (P/E) | 0.964 | 0.109 | 1.007 | 0.493 | VE (P/E) | 0.716 | 0.158 | 0.579 | -0.139 |
| VE (M.B.) | 1.054 | 0.104 | 1.096 | 0.612 | VE (M.B.) | 0.740 | 0.124 | 0.630 | -0.071 |
| VE (REV) | 6.640 | 0.061 | 4.036 | 6.041 | VE (REV) | 1.373 | 0.062 | 0.631 | 0.10 |
| VE (EBITDA) | 8.180 | 0.067 | 3.900 | 7.571 | VE (EBITDA) | 1.455 | 0.068 | 0.506 | 0.11 |
| **Arithmetic Mean** | | | | | **LN-Mean** | | | | |
| VE (P/E) | 1.560 | 0.154 | 1.544 | 1.302 | VE (P/E) | 0.975 | 0.121 | 1.009 | 0.505 |
| VE (M.B.) | 2.309 | 0.109 | 2.191 | 2.144 | VE (M.B.) | 1.065 | 0.113 | 1.117 | 0.630 |
| VE (REV) | 62.596 | 0.031 | 35.219 | 62.476 | VE (REV) | 6.595 | 0.043 | 3.894 | 5.989 |
| VE (EBITDA) | 57.056 | 0.036 | 25.827 | 56.897 | VE (EBITDA) | 7.774 | 0.040 | 3.719 | 7.155 |

Table 3: Valuation Error distribution under the four models

| | EV - M.B. | EV - P/E | EV - P/REV | EV - P/EBITDA |
|---|---|---|---|---|
| EV - M.B. | | 0.76 | 0.21 | 0.16 |
| EV - P/E | 0.51 | | 0.23 | 0.21 |
| EV - P/REV | 0.14 | 0.07 | | 0.83 |
| EV - P/EBITDA | 0.08 | 0.05 | 0.82 | |

Table 4: Correlations between simple multiple valuation outcomes

### 5.2 Combination of simple multiple valuations

Multiples hold incremental information that is based on its underlying fundamentals. Depending on the type of information, certain multiples might see an overlap in the fundamentals that they are based upon. If this captured information is to be the same in all multiples, the correlations as shown in table 4 should equal the unit. However, this is not the case and thus indicate that certain information is captured by some multiples but not all. This gives me a very viable reason to explore whether a combination of simple multiple valuations might be better able to predict the equity value of a firm.

First, a linear price-deflated regression is considered in which the first-day closing price is the dependent variable and the simple multiple valuation outcomes, based on the harmonic mean, are the independent variables. The estimated coefficients of the regressions are the weights of the simple multiple valuation outcomes for each observation. This regression is performed on both the entire cross-section as well as per industry. As only older firms than the valued firm can be used to estimate equity value, for each regression iteration the valued firm itself is removed from the group of comparable firms. All regressions have been performed with and without an intercept. For most of the analyses, it is theoretically impossible for the independent variables to take a value of zero. Because of this, the produced intercept has meaningless value and should not be interpreted. In these cases, the no-intercept counterpart of the regression provides far more useful data and is therefore chosen as the preferred analysis. Also, for all (linear) models the resulting R-squared, defined as the proportion of variance in the dependent variable that is predictable from the independent variables, is higher.

Second, non-linear price-deflated regressions are considered to derive the appropriate weights of the simple multiple valuation outcomes. The estimated equity values produced by the REV & EBITDA multiples have shown to be of very little accuracy. Therefore, they produce some significant outliers that distort the data. Another characteristic of the valuation outcomes based on these multiples is that they do not follow a normal distribution. This gives me reason to transform the variables in order for them to follow a normal distribution and to see whether these transformed values are better able to estimate equity value. The observed first-day closing price has a slightly skewed distribution to the right and is therefore also candidate for a logged transformation. Out of the several models on page seven, the following versions will be examined:

- **Model (a)** in which the simple multiple valuation outcomes under either *REV*, *EBITDA* or both methods are log-transformed (*Lin-Log.R / Lin-Log.E / Lin-Log.RE*);
- **Model (b)** in which the price is log-transformed (*Log-Lin*);
- **Model (c)** in which the price and simple multiple valuation outcomes of *REV* and *EBITDA* are log-transformed (*Log-Log*).

Table 5 presents the distribution of valuation errors for all models. The valuation error of the simple multiple valuation is calculated as the average of the valuation outcomes based on the M.B. and P/E multiple. With the mean of valuation errors close to zero, the Lin-Log.RE model gives a good unbiased estimate of the valued firms' price. Interesting to see is the median of the valuation errors under the simple multiple valuation, this model is the only one to produce a negative number. This may indicate several things; such as systematic higher overpricing or significant outliers on the left-tail of the distribution. The method of combining simple multiple valuation outcomes produce slightly lower absolute valuation errors for the linear and Log-Lin.RE model compared to the SMV model. However, this is compensated by a wider dispersion in valuation errors and thus these differences seem quite marginal.

| | MAVE | 15%AVE | IQVE | MEAN | MEDIAN |
|---|---|---|---|---|---|
| VE (Log-Lin) | 4.536 | 0.119 | 2.699 | -0.859 | 0.650 |
| VE (Log-Log) | 2.105 | 0.064 | 1,176 | -1.196 | 0.529 |
| VE (Lin-Log.E) | 0.992 | 0.144 | 0.941 | -0.467 | 0.177 |
| VE (Lin-Log.R) | 0.975 | 0.143 | 0.949 | -0.456 | 0.171 |
| VE (Lin.Log.RE) | 0.719 | 0.148 | 0.698 | -0.094 | 0.296 |
| VE (Lin) | 0.727 | 0.150 | 0.700 | -0.114 | 0.285 |
| VE (SMV) | 0.728 | 0.142 | 0.605 | -0.106 | -0.462 |

Table 5: Distribution of valuation errors

Table 6 presents the test statistics of the Diebold-Mariano tests for the valuation error comparison between the simple multiple valuations and the linear model. Table 7 presents the test statistics for the valuation errors comparison between the different logarithmic models. A significant negative (positive) statistic indicates that the model in the row (column) produces significantly better valuation outcomes.

As presented in table 6, previous findings concerning the superiority of the M.B. and P/E multiples are confirmed. Judging by the high test statistics, the linear model produces significantly better valuation outcomes than those models based on the REV and EBITDA multiple. However, no significant distinction can be made between the performance of the linear model and the best performing simple multiple valuations. Table 7 shows the Lin-Log.RE model outperforms any of the other log-transformed regression models. This result suggests that taking the log of the simple multiple valuation outcomes based on both the REV and EBITDA multiple yield significantly higher valuation accuracy compared to the other logarithmic regressions.

| | VE (M.B.) | VE (P/E) | VE (P/REV) | VE (P/EBITDA) | VE (Lin) |
|---|---|---|---|---|---|
| VE (M.B) | | -0.331 | -5.123*** | -5.129*** | -0.435 |
| VE (P/E) | | | -5.391*** | -5.921*** | -0.217 |
| VE (P/REV) | | | | -0.790 | 6.724*** |
| VE (P/EBITDA) | | | | | 7.113*** |
| VE (Lin) | | | | | |

Table 6: test statistics for valuation error comparison between SMV and linear regression methods

| | VE (Log-Log) | VE (Log-Lin) | VE (Lin-Log.E) | VE (Lin-Log.R) | VE (Lin-Log.RE) |
|---|---|---|---|---|---|
| VE (Log-Log) | | 1.991*** | 3.121*** | 3.185*** | 9.682*** |
| VE (Log-Lin) | | | 2.482*** | 2.677*** | 8.525*** |
| VE (Lin-Log.E) | | | | 0.229 | 3.295*** |
| VE (Lin-Log.R) | | | | | 3.019*** |
| VE (Lin-Log.RE) | | | | | |

Table 7: test statistics for valuation error comparison between logarithmic models

The results of the tables above give a good impression of the ranking between the SMV and linear models and within the logarithmic models. A final Diebold-Mariano test is performed to examine the difference in means of absolute valuation error between the linear model, the SMV models based on M.B. and P/E multiple and the Lin-Log.RE model. An insignificant test statistic of -0.090 for the comparison between the linear and Lin-Log.RE model indicates that the absolute valuation errors do not statistically differ under the two models, failing to reject the main hypothesis.

### 5.3 Industry-based comparables

The second hypothesis that is tested considers choosing comparable firms on basis of industry classification. For all industries that met the criteria of sufficient comparable firms, new equity values have been estimated on basis of the four best performing models on the cross-sectional sample. Table 8 presents the distribution of valuation errors for the industry-bound sample based on the summarized result from each industry. The table suggests that all models have less valuation accuracy compared to their cross-sectional counterpart. Untabulated statistical tests confirm this as all t-tests and Diebold-Mariano tests produce statistically significant scores. Furthermore, there are no particular industries in which a certain multiple provides significant better valuation accuracy. Following these results, the hypothesis that valuation accuracy improves when using comparable firms based on industry is rejected.

| | MAVE | 15%AVE | IQVE | MEAN | MEDIAN |
|---|---|---|---|---|---|
| SMV (M.B.) | 0.970 | 0.115 | 0.677 | 0.280 | 0.053 |
| SMV (P/E) | 1.204 | 0.117 | 0.730 | 0.476 | 0.101 |
| Linear | 1.230 | 0.170 | 1.008 | -0.742 | 0.085 |
| Lin-Log.RE | 1.129 | 0.154 | 0.994 | -0.422 | 0.069 |

Table 8: Distribution of valuation errors of industry-bound sample

### 5.4 Recent comparable firms

Firms seem to time their IPOs in periods in which many other firms conduct their IPOs. This is not a coincidence, as explained by (Chemmanur & He, 2011), but a very deliberate action with the goal of maximizing firm value. This invasion of IPOs, called a 'hot market' leads to a collective optimism among investors and may in turn result in higher closing prices or post IPO excess returns. (Helwege & Liang, 2004) found in their study on hot and cold markets that IPOs conducted in times of a hot market have significantly more underpricing. To test for differences among these groups in my study, I have performed the same analyses as shown above with a different group of comparable firms. Since there is not set window for the length of a hot or cold market, I have used IPOs that went public in the two years prior to the valued firm its IPO as comparables. Following the performance of the industry-specific group of comparable firms, I have performed these analyses only on the cross section.

Table 9 presents the distribution errors of the above-mentioned analyses under the different models. The distribution indicates better performance under *all* methods when estimating equity value using a set of recent comparable firms as opposed to comparable firms overall. The MAVE of the Linear model is almost 0.15 lower than the value reported in table 5. The percentage of sample within range of 15% of actual value is more than 6% higher for the Linear model. As opposed to the results of table 5, the Linear model clearly seems to outperform some of the other models when using recent comparable firms.

To test the magnitude of the differences among the models, several Diebold-Mariano tests have been performed. Between the group with regular comparable firms and this group, the Linear and Lin-Log.RE model significantly perform better than their counterpart. Within this group, no statistically significant difference can be found between the MAVE of the SMV (P/E), SMV (M.B.) and Lin-Log.RE model.

These results allow me to partially reject the third hypothesis which suggests no difference in valuation accuracy when using recent comparable firms instead of regular comparable firms. Why this difference does not hold for the other two models is not really clear. More research on this aspect of multiple valuation should give interesting insights and might pave the way for more complex ways of determining the proper group of comparable firms.

In order to test for whether there is more underpricing during hot IPO markets, I have classified the IPOs into ten categories based on their IPO year. Number 1 indicates the period 2019-2017, number 2 indicates 2017-2015 and so on. Next, I have performed an ANOVA to check for a difference between offer price and price (Pdif) between the ten groups. The ANOVA indicates that there is a significant difference among the groups, the plot in the appendix shows this difference in prices. The average underpricing in the sample is 0.89 dollars, which corresponds to a value of 13.3% relative to the average price.

| | MAVE | 15%AVE | IQVE | MEAN | MEDIAN |
|---|---|---|---|---|---|
| SMV (P/E) | 0.703 | 0.186 | 0.835 | -0.124 | -0.384 |
| SMV (M.B.) | 0.625 | 0.191 | 0.742 | -0.119 | -0.320 |
| Lin-Log.RE | 0.610 | 0.193 | 0.735 | -0.074 | 0.284 |
| Lin | 0.584 | 0.211 | 0.882 | -0.098 | 0.299 |

Table 9: Distribution of valuation errors using recent comparable firms

### 5.5 Firm age and issue effects

As much of previous literature has stated, younger firms are often more difficult to value when conducting IPOs. Reason for this may be a lack of financial information and larger information asymmetry between the firm and investors. To examine whether these empirical findings also hold in this study, two tests will be performed.

First, a variable is created that measures the difference between a firm its founding date and IPO date in months. A regression is performed in which the absolute valuation error is the dependent variable and the difference in founding- and IPO date is the independent variable. Based on the explanation above, a negative coefficient for the independent variable is expected.

Second, a dummy variable is created that distinguishes a firm between being either young or old. There is no universally acknowledged age for a firm to be considered old as firms go through multiple life-cycle stages and sometimes enter these stages more than once. Therefore, the threshold to be set is quite subjective. Also, an IPO itself is an important financing decision which, in many cases, indicates a change of the firm its development and could therefore be seen as the firm entering a new business stage (Yan & Zhao, 2009). According to the distribution in the data the threshold is set at seven years. As a result, little under a quarter of the sample is classified as a young firm. Next, an ANOVA is performed to see whether the mean absolute valuation error significantly differs among the two groups. The absolute valuation errors that are compared are those computed under the four best performing models.

Table 10 shows the summarized regression output of the four regressions. For the purpose of simplicity, only the intercept of the simple multiple valuation model based on the P/E multiple is shown. However, all four regressions have significant intercept coefficients that lie around this number. The full regressions are shown in the appendix. Table 11 shows the difference in MAVE for young and old firms. The asterisks in the column indicate a significant difference in MAVE between the two groups.

These results are consistent with findings in previous studies and confirm valuation accuracy does improve with firm age at IPO. Interesting to see is that no significant difference between the two groups can be found for the MAVE calculated under the averaged M.B. multiple. This result is quite surprising since the fundamental financial information the M.B. multiple is calculated upon would be less accurate for younger firms, as is for the other multiples. This ambiguous result causes the third hypothesis to be rejected.

| | Coefficient | Std. Error | t-statistic | P-value |
|---|---|---|---|---|
| Intercept | 0.739 | 0.0370 | 19.998 | 2e-16*** |
| D_DIF (AVE – M.B.) | 0.001 | 0.001 | 1.542 | 0.123 |
| D_DIF (AVE – P/E) | -3.577e-4 | 1.351e-4 | -2.647 | 0.008*** |
| D_DIF (AVE – Lin-Log.RE) | -6.328e-5 | 1.224e-4 | -0.517 | 0.605 |
| D_DIF (AVE – Lin) | -6.115e-5 | 1.231e-4 | -0.497 | 0.619 |

Table 10: Summarized regression output of valuation error on firm age at IPO

| | MAVE (M.B.) | MAVE (P/E) *** | MAVE (Lin-Log) *** | MAVE (Lin) *** |
|---|---|---|---|---|
| Young | 0.720 | 0.588 | 0.664 | 0.633 |
| Old | 0.755 | 0.843 | 0.774 | 0.820 |

Table 11: Comparison of MAVE between young and old firms

Finally, the effect of the number of shares retained by pre-issue shareholders on equity value is examined. In line with the signaling theory, a larger portion of equity retained indicates a positive signal to investors by management as they do not use the IPO as a way of dumping stock. According to this theory, greater relative ownership would result in a higher first-day closing price.

A regression has been performed in which the difference between offer price and first-day closing price is the dependent variable and the equity retained (EQRET), expressed in decimal numbers between zero and one, is the independent variable. A higher price would indicate more overpricing or less underpricing and therefore a positive coefficient for equity retained is expected. It is not possible for the independent variable to take a value of zero due to lockup constrictions imposed by shareholders for the obvious reasons stated above. For this reason, the regression is performed without an intercept as this variable would not have meaningful value.

Table 12 shows the results of the regression. A significant positive relationship is found between the portion of equity retained by pre-issue shareholders and the pricing difference between offer price and first-day closing price. These findings are in line with the expectations and seem to give confirm the theory derived from the signaling theory. Of course, over- / underpricing is caused by a lot more than just this variable. Untabulated results indicate that this relationship also holds within most industries.

| | Coefficient | Std. Error | t-statistic | P-value |
|---|---|---|---|---|
| EQRET | 1.207 | 0.0729 | 16.54 | 2e-16*** |

Table 12: Regression output of price difference

## 6 Conclusion

This paper examines a different approach to conventional multiple valuation by combining several simple multiple valuation outcomes. The value added by this study lies in the fact that also non-linear combinations are considered. Furthermore, effects of comparable firms, statistical measures and firm size on valuation accuracy are examined.

I find that the use of the harmonic mean as the statistical measure to average comparable firms their multiples produces the lowest valuation errors. Out of the examined multiples, the book value and earnings multiples provide the most accurate simple multiple valuations, followed by the revenue and cash flow multiples. This ranking seems to be robust for the majority of my sample. These results may indicate that revenue and EBITDA might not be proper representatives of a firm its equity value.

No significant difference can be found between the performance of the simple multiple valuation, the linear model and the model which takes the logarithm of the valuation outcomes based on the revenue and cash flow multiples. However, when considering only recent comparable firms for the analyses, the valuation errors significantly drop for the combined models. These results suggest that market sentiment might have a significant effect on the performance of certain multiples.

Significantly higher underpricing is found in periods in which a relatively large number of IPOs are conducted. The same is observed when a larger number of shares is retained by the pre-issue shareholders. This may indicate that the signal sent from shareholders to investors has a positive effect on the closing price.

My results regarding the valuation accuracy for older firms are consistent with previous literature, stating that older firms are easier to value and therefore possess smaller valuation errors. This does not hold for the model based on the book value multiple, which indicates that part of the information this multiple is built upon does not reflect all information of the other equity multiples.

Multiple valuation is for the majority popular because of its simplicity. The analyses and transformations that are performed in this study slowly make the method deviate away from this term. A proper balance between accurate valuation and simplicity should be achieved in order for the model to be fully appreciated.

Whether the results found in my study can be generalized to other multiples is to be examined. This study has put its focus on general relations and a large number of aspects regarding multiple valuation, it may have missed more subtle relations that are easier to find in smaller sample research. Exploring more thoroughly to what extent the effect of the chosen comparable firms on valuation accuracy can be improved is an interesting path open for future research.

# 7 Appendix

| | Df | Sum Sq | Mean Sq | F value | Pr( $F$) |
|---|---|---|---|---|---|
| Agetest$AgeGroup | 1 | 294 | 194.12 | 4.827 | 0.0281* |
| Residuals | 4403 | 177059 | 40.21 | | |

Table 13: ANOVA results of underpricing difference among groups

| | Estimate | Std. Error | t value | Pr( $\|t\|$) |
|---|---|---|---|---|
| Intercept | 0.739 | 0.0370 | 19.998 | 2e-16*** |
| FullSample$D_DIF | -3.577e-4 | 1.351e-4 | -2.647 | 0.008*** |

Table 14: Regression result of firm age on AVE of the P/E model

| | Estimate | Std. Error | t value | Pr( $\|t\|$) |
|---|---|---|---|---|
| Intercept | 0.676 | 0.0320 | 21.147 | 2e-16*** |
| FullSample$D_DIF | 1.800e-4 | 1.169e-4 | 1.539 | 0.124 |

Table 15: Regression result of firm age on AVE of the M.B. model

| | Estimate | Std. Error | t value | Pr( $\|t\|$) |
|---|---|---|---|---|
| Intercept | 0.683 | 0.034 | 20.277 | 2e-16*** |
| FullSample$D_DIF | -6.115e-5 | 1.231e-4 | -0.497 | 0.619 |

Table 16: Regression result of firm age on AVE of the linear model

| | Estimate | Std. Error | t value | Pr( $\|t\|$) |
|---|---|---|---|---|
| Intercept | 0.677 | 0.035 | 20.205 | 2e-16*** |
| FullSample$D_DIF | -6.328e-5 | 1.224e-4 | -0.517 | 0.605 |

Table 17: Regression result of firm age on AVE of the logarithmic model

| f1 = Linear model | f2 = Lin.Log.RE model | |
|---|---|---|
| Statistic = -0.089719 | forecast horizon = 1 | p-value = 0.464 |
| Alternative hypothesis = forecast f1 is more accurate than f2. | | |

Table 18: Diebold-Mariano test between linear and logarithmic model

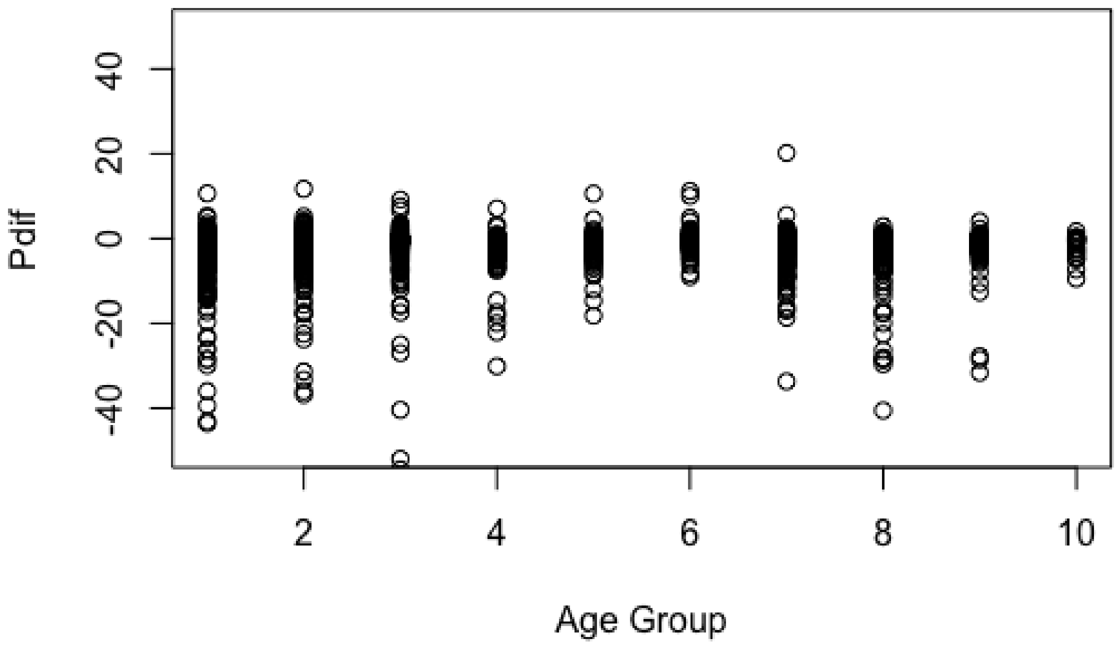


Figure 1: Underpricing difference between age groups

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