ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis

Factors Relevant for Deciding P/E Ratios

Name Student: Ahrim Kim

Student ID number: 510186

Supervisor: Rogier Quaedvlieg

Second Assessor: Ruben de Bliek

Abstract

Although a DCF analysis can provide more precise and detailed analysis about a company, multiple analysis has an important role in setting a benchmark for key ratios and checking for possible overestimation or underestimation of value. Especially, the benchmark ratio such as the P/E ratio helps setting realistic stock price in case of IPOs. With the recognition of the importance of setting a benchmark through multiple analysis, this paper discusses about choosing the best standards for selecting comparable firms, especially when predicting the P/E ratios. This paper also looks into revised methods such as adjusting the P/E ratios after selecting comparables or predicting the P/E ratios using the best-fit regression. The results show that using the regression model significantly enhances the accuracy of the prediction compared to the conventional multiple analysis of choosing comparables based on the industry classification.

Contents

1. Introduction to research question

Multiple analysis is acknowledged for its convenience in estimating enterprise value. It is widely used to provide guidelines for valuations of IPOs, SEOs, M&As and many other fundamental analyses. Although it does not consider individual specific factors of companies as in a DCF-based valuation, which includes future growth rates and WACCs, it provides great benchmarks with regards to appropriate value ranges of the companies. Especially when historic stock prices are not given, as in the case of an IPO, multiple analysis is a good way of anticipating market's price discovery. Besides, in combination with peer company comparisons, DCF valuation obtains a realistic basis of the estimation, and correct its possible over or underestimation of accounts used for valuation in case the enterprise values derived from DCFs show huge difference to peer companies. Multiples are also an important approach for analysts to predict an appropriate stock price and publish buy or sell recommendation.

According to an article published by Mckinsey & Company in 2005, comparing multiples with competitors enhances the accuracy of DCF forecasts and is helpful for stress-testing the cash flow forecasts. In addition, it can help executives understand differences of multiples when compared with competitors and it can produce insights into the core factors that create value in each industry (Goedhart et al., 2005).

Therefore, it is crucial to understand what the main drivers for multiple values are as it is the starting point of a reliable benchmark for a DCF valuation. For a multiple analysis to be a reliable basis for DCF models, comparables should be selected based on the relevant factors that affect the multiples.

One of the most common ratios used for multiple analysis is the P/E ratio (Price-to-Earnings Ratio), which can provide stock price ranges in the case of stock issuance, stock acquisitions, or buy and sell recommendations. However, despite the wide usage of the multiple analysis, there does not seem to be a clear guidance with regards to what variables affect the cross-sectional differences of P/E ratio or standards for peer group selection. The frequently used standards are industry, company size, and company performance such as growth rate or profitability.

I would like to raise a research question based on this problem.

What is the best way to choose the benchmark P/E ratio?

The main purpose of this paper is to find the method that best forecasts the P/E ratios of the target company to provide a useful benchmark for DCF valuation. In order to do so, this paper first tests the standards that are helpful in selecting peer companies with similar P/E ratio in the same industry. Also, it is tested whether replacing the earnings value in the P/E ratio with different values can enhance the prediction accuracy. In addition to that, this paper tests the regression-based prediction using the best-fit regression. This paper aims to understand the factors that drive the differences in P/E ratios in the market, which will provide insights to investors and students studying finance and shed further light on the factors generating value for companies.

Through this thesis, I can combine and re-examine the results from different studies, using different datasets other than the US market data, which were used in previous studies.

2. Literature Review

2.1. Calculating the Value of Total Shares (DCF)

As multiple analysis is often used as a complementary analysis for the DCF analysis, it is useful to obtain an understanding of the analysis first.

The following method of DCF is widely agreed upon, although some detailed estimations of each accounts for valuation can differ from company to company. In a DCF analysis, one calculates the enterprise value based on future earnings and adds the value of growing assets from operation to the current value of net non-operating assets. It is common to use earnings predictions for the next five years and the terminal value, which is defined as the discounted earning of the period beyond the five years. The WACC is used as the discount rate and the terminal growth rate needs to be estimated for the calculation of the terminal value. The operating enterprise value is acquired by adding up the discounted earnings of five years and the terminal value. The total enterprise value is the explained operating enterprise value combined with net non-operating assets. The total equity value is the total enterprise value less non-equity claims which is majorly net debt calculated by total liability less cash and cash equivalents (Damodaran, 2016).

Considering the stages of valuation in the DCF model, three factors mainly affect the valuation of stocks, which are the free cash flow, the discount rate, and the growth rate.

According to Damodaran (2016), free cash flow to equity starts with net income. From the net income, capital expenditures and investment in working capital are subtracted as they are cash outflows. After that, non-cash charges such as depreciation and amortization are added back. New debt less debt repayment is also a cash inflow. With a constant growth model, the current stock value is calculated according to the following formula: FCFE/(WACC-g). The g denotes the constant growth rate of the firm.

From this valuation procedure, it can be suggested that replacing net income from P/E ratio with the FCFE of the current year can reduce prediction errors of P/E ratio. It is important to note the calculation for prediction error is elaborated in section 3. Data & Method.

However, Koller et al. (2015) assert that FCF calculation should start from EBITA. Due to the fact that physical assets are capitalized on the balance sheet and its values wearing out are recorded, depreciation can be included as an operating expense. On the contrary, amortizations are not capitalized and instead are expensed, and using EBIT can double penalize the cash outflow by lessening both amortization and reinvestment cost. It can be tested if replacing net income from P/E ratio with the FCF of the current year calculated by Koller's method reduces prediction errors of P/E ratio.

Koller et al. (2015) also mention that as an individual beta for each firm is hard to be measured, and an industry median can be used. Therefore, cost of equity is either the same or similar for the firms in the same industry, as companies in Europe thought to be sharing the risk-free rate of the German bond yield. There can be variances in cost of debt and tax rate, but in this paper, the difference in WACC is assumed to be solved mostly by taking the industry into account when selecting peer companies. As leverage determines the ratio of the cost of debt and the cost of equity, this can be considered as a relevant factor to the P/E ratio as well.

2.2. Previous Studies on Peer Group Selection and Prediction Accuracy of P/E ratio

There have been a few interesting preceding studies about improving the prediction accuracy of the P/E ratio.

Kim and Ritter (1999) tested whether adjusting the P/E ratio by using the forecasted earnings instead of trailing earnings can increase the valuation accuracy. From the sample of 1992-1993 IPOS, the firms with the same four-digit SIC code were selected as comparables. The authors used only five of them with the closest sales in the recent 12 months if there were more than five in the same industry. The prediction errors were measured as the logarithm of the median P/E ratio of the five comparables minus the natural logarithm of the target P/E ratio. The results show that the prediction errors were greatly reduced when the authors used the forecasted earnings. This study can be re-examined with a different dataset that not only contains IPOs.

Another research about growth rates and the P/E ratio was carried out by Boatsman and Baskin (1981). In the empirical test, for each target one firm in the same industry with the most similar ten-year average earnings growth rate was matched and prediction errors were calculated. The prediction error, which is the percentage of the absolute difference between the target firm P/E ratio and the matched firm P/E ratio compared to the target firm P/E ratio, decreased compared to the prediction error acquired from a random company in the same industry. Boatsman and Baskin's study has a major limitation as it uses only one comparable firm which is usually not the case when selecting peer groups.

There are also studies and articles related to profitability. Bothra et al. (2019) find that, although it is true that multiples differ between industries, they vary greatly even within an industry as they reflect different growth rates and profitability. Achieving the industry-average expected performance is required for a company to attain industry-average multiples. An empirical study of Dittmann and Weiner (2005) found that selecting the peer group using the ROA outperforms selecting the peer group based on the industry standard when considering the EV to EBIT multiple. After getting the harmonic mean of the multiple, the absolute prediction error (APE) was calculated as the absolute value of the percentage of the harmonic mean less the actual value of the target firm to the actual value as the following function: |(harmonic mean-actual)/actual|.

Alford (1992) used the firm size represented by total assets to estimate the firm's risk and ROE for profitability (or earnings growth). The APE was calculated using the median P/E ratio of the peer group. In the paper, choosing firms in the same industry among the 2% with the closest total assets performed worse in terms of APE. Besides, choosing firms in the same industry among the 2% with the closest ROE did not perform better than just choosing based on the industry classification. However, this study did not limit the actual difference of total assets or ROE, and even among the 2% firms with the closest value can vary a lot in terms of total assets or ROE.

Referring to the previous studies mentioned above, whether profitability affects the P/E ratio prediction can be tested based on the four representative measures for profitability: net profit margin, ROA, ROE, and ROIC. In addition, a commonly used standard, size, can also be tested if it adds value when selecting comparable companies.

To grasp a deeper insight on which factors drive the P/E ratio, we can look into regression models.

Bohjraj and Lee (2002) introduced an interesting way of choosing comparables, which is using a warranted multiple. First of all, the authors regressed the enterprise-value-to-sales ratio (EVS) on the harmonic mean of the EVS in the same industry, the harmonic mean of the price-to-book ratio, the profit margin, the industry-adjusted growth forecast, the book leverage, the return on net operating assets, the ROE and the R&D expense. With the coefficient from the regression, they generated the warranted EVS of each target firm, and chose those firms with the closest EVS to the warranted multiple as comparables. This method showed an improvement in prediction accuracy of one, two or three years ahead EVS. This finding implies that using a regression model is not only insightful in finding explanatory variables for each multiple, but also in predicting them and reducing prediction errors.

Another paper by Ohlson (1990) included the expected dividend pay-out rate and the expected earnings growth rate in the function expressing a P/E ratio after using risk-free rate and risk adjustments.

With the discussion so far, the following three hypotheses can be suggested.

Hypothesis 1. Adding long-term growth rate, three-year average growth rate, five-year average growth rate, net profit margin, ROA, ROE, ROIC, total assets or market capital to the industry standard for peer company selections reduces the prediction errors of the P/E ratios compared to selecting comparables solely based on the industry.

Hypothesis 2. Replacing the earnings of the P/E ratio with FCF from Damodaran's method, FCF from Koller's method, or 12-month forward EPS after selecting comparables based on the industry reduces the prediction errors compared to using the median P/E ratio of the companies in the same industry.

Hypothesis 3. Using the best-fit regression function for the prediction reduces the prediction errors of the P/E ratio compared to the peer company selection based on the industry.

3. Data & Method

3.1. Data Description and Data Reorganization

The empirical research considers 1414 companies that are listed on the Euronext, Euronext Growth, and Euronext Access. Among the 1414 companies, the companies that did not have the accounting information or the P/E ratio available are excluded. The highest 4% and the lowest 4% of the companies in terms of the P/E ratio are removed to exclude the outliers. There are 585 companies left in the year 2016, 594 companies in 2017, and 600 in 2018. The P/E ratios of the companies are ranged in between 4 and 95.

Using the ISIN code as company identifier, the Standard Industry Classification (SIC) code was pulled from Capital IQ via the Wharton database. Quarterly and yearly data of accounting information from 2011 to 2019 are downloaded from the same database. In particular, these include total asset, total shareholders' equity, current debt, long-term debt, net income, earnings before interest and tax (EBIT), R&D expense, invested capital, depreciation and amortization(D&A), operating tax, capital expenditure (CAPEX) and change in working capital. From this information, average growth rates of three and five years, net profit margin, ROA, ROE, ROIC and leverage can be derived. The calculations are further elaborated in Table 1. Furthermore, the stock price, market capital, price-to-earnings ratio, 12-month forward dividend yield, and long-term growth rate (LTG) are downloaded from Datastream. Lastly, IBES was used to extract the 12-month forward EPS.

The P/E ratios at the end of the year (t) for the target companies are predicted using the peer company selection based on the accounting information of Q4 from the previous year and Q1, Q2, Q3 of the present year. The accounting information summed up are the yearly accounting data available at time t.

Table 1 Calculations of Variables

Variable	**Calculations**
$Leverage_{t,n}$	$\frac{Current\ Debt_{t,n} + Long\ term\ Debt_{t,n}}{Total\ Shareholders'Equity_{t,n}}$
$Three\ year\ average\ growth\ rate_{t,n}$	$\frac{(Revenue_{t,n} - Revenue_{t-3,n})}{Revenue_{t-3,n}} \times \frac{1}{3}$
$Five\ year\ average\ growth\ rate_{t,n}$	$\frac{(Revenue_{t,n} - Revenue_{t-5,n})}{Revenue_{t-5,n}} \times \frac{1}{5}$
$ROA_{t,n}$	$\frac{Net\ Income_{t,n}}{Total\ Assets_{t,n}}$
$ROE_{t,n}$	$\frac{Net\ Income_{t,n}}{Total\ shareholders'equity_{t,n}}$
$ROIC_{t,n}$	$\frac{EBI_{t,n}}{Invested\ Capital_{t,n}}$

$Net\ Profit\ Margin_{t,n}$	$\frac{Net\ Income_{t,n}}{Revenue_{t,n}}$
$Damodaran\ FCF_{t,n}$	$Net\ Income_{t,n} - Change\ in\ Net\ Working\ Capital_{t,n} - CAPEX_{t,n} + Depreciation\ and\ Amortization_{t,n} + New\ Debt_{t,n} - Debt\ repayment_{t,n}$
$Koller\ FCF_{t,n}$	$EBITA_{t,n} - Operating\ Tax_{t,n} - Change\ in\ Net\ Working\ Capital_{t,n} - CAPEX_{t,n} + New\ Debt_{t,n} - Debt\ repayment_{t,n}$

**The letter t denotes the time on a yearly basis and the letter n denotes each company in the sample.

3.2. Comparing the Prediction Accuracy of the Peer Company Selection Standards

Peer companies are selected based on the accounting information available at the end of the year. The value of each accounts is the yearly amount, which means the data of Q4 from the previous year and the Q1 to Q3 of the present year are summed up. The LTG and the 12-month forward EPS are predicted at the start of the Q4. The P/E ratios of the peer companies are the values at the end of Q4.

The firms are categorized in the same industry group using the first two digits of the SIC code, which denote the major industry group the firms belong to.

In order to choose comparables with similar sizes, either the total assets or the market capital was considered. If a firm has more than 70% and less than 130% of the target firm's value of total assets or market capital, the firm is considered to be of similar size with the target firm.

With regards to measurement of the same level of the growth rate, the following method is used. For the three-year average growth rate, firms are divided into three groups: below-zero, low, and high. The below-zero group has the average growth rate smaller than zero, and among the rest, the lowest half are categorized in the low group while the highest half were categorized in the high group. This is the same for the five-year average growth rate and the long-term growth rate. The firms in the same group are considered to have the same level of the growth rate.

To classify the companies into the same level of profitability, with respect to each standard of profitability (Net profit margin, ROA, ROE and ROIC), the firms are divided into four groups: below-zero, low, middle and high. The below-zero group has the profitability rate below zero, and among the rest, the top one-third go to the high group, the bottom one-third go to the low group, and the rest go to the middle group.

To decide on the peer companies, five main categories are used. The most basic selection standard is the industry the company belongs to. Then, it is tested whether each additional standard mentioned in the hypothesis 1 in section 2 adds a predictive value to peer group selection. In order to test for the predictive power, prediction errors are computed according to the following formula:

$$Prediction\ Error_{t,n} = \left| \frac{Median\ P/E\ of\ peers_{t,n} - P/E\ of\ the\ target_{t,n}}{P/E\ of\ the\ Target_{t,n}} \right|$$

Since the distance from the actual P/E ratio of the target, not the sign of the error, is the main interest, I take the absolute value of the prediction error. Also, the comparative distance compared to the target's P/E ratio is used by converting the distance to a percentage of the actual P/E ratio.

To test if the prediction errors are significantly reduced by adding each standard, the paired t-test is used. The paired t-test tests if the means from the two matched sets of data are statistically significantly different.

3.3. The Method of Adjusting the P/E ratio

To test the hypothesis 2, the peer companies are selected based on the industry only, but the P/E ratios are adjusted. The stock price per share is divided either by per share FCF calculated with Damodaran's method, by per share FCF calculated with Koller's method, or by the 12-month forward EPS predicted at the beginning of the 4Q. The median of the adjusted P/E ratios are used to calculate the prediction errors. The paired t-test is used to test if the adjustment is effective in reducing the prediction errors.

The prediction value is the median P/E ratio of the peer companies, and the prediction is carried out only if there are more than one peer companies to avoid one company's dominant (biased) effect on the prediction. There are also companies without data for the additional standards. As a result, the observations used for testing the hypothesis 1 and 2 are smaller than the number of companies in the sample.

3.4. Testing the Prediction Accuracy of the Best-Fit Regression

The last method to be tested is using the best-fit regression to predict the P/E ratios of the next quarter.

Based on the literature review, the explanatory variables are selected among leverage ratio, R&D expense, ROA, ROE, ROIC, net profit margin, LTG, three-year average growth rate, five-year average growth rate, 12-month forward dividend yield, 12-month forward EPS, total assets, and market value. Especially for 12-month forward EPS, it is also tested whether it is better to use the percentage difference between the 12-month forward EPS and the actual EPS.

To find the best-fit regression, the yearly R&D expense, ROA, ROE, ROIC and net profit margin are calculated using the accounting information of the previous year's Q4 and the present year's Q1 to Q3. The leverage ratio, total assets, and market value are the values at the end of Q3 of the present year. The three-year average growth rate and the five-year average growth rate are the revenue growth till the Q3 of the present year compared to the same quarter from three or five years ago. The LTG, the 12-month forward dividend yield, and the 12-month forward EPS are the values estimated at the start of the Q4. The P/E ratios are the values at the end of the Q4.

Starting from a regression of the P/E ratio against dummy variables for industry, each explanatory variable is added or removed from the regression to find the best-fit regression. The criteria of choosing the best-fit regression are R squared, adjusted R squared, AIC and BIC. Pearson correlation and the Variance Inflation Factor (VIF) are used to test for multicollinearity.

After choosing the best-fit regression model, the P/E ratios at the end of the Q1 of the following year are predicted with the coefficients estimated from the previous data. The variables used for the prediction are the same as the ones used for fitting, but the LTG, the 12-month forward dividend yield, and the 12-month forward EPS are updated with the new values estimated at the beginning of the Q1. The prediction errors are calculated as before, and a paired t-test is carried out to compare with the peer group selection method using only the industry standard.

4. Result

4.1. Peer Group Selection

Whether an additional standard of the company size, the growth rate, or profitability enhances the prediction accuracy is tested with the paired t-test, and the results are displayed in the table 2, 3, and 4. The full tables for the test results can be found in appendix A, B and C for the year 2016, 2017 and 2018 respectively.

The mean difference is the mean prediction error of the method using SIC code only subtracted by the mean prediction error of the method using one more additional standard other than the SIC code. P-value 1 denotes the p-value of the hypothesis that the mean difference is smaller than 0, which means the p-value of the hypothesis that the prediction error is increased after adding a standard for the peer group selection. P-value 2 denotes the p-value of the hypothesis that the mean difference is greater than 0, which means the p-value of the hypothesis that the prediction error is decreased after adding a standard for the peer group selection.

Table 2 The Paired T-test of the Prediction Errors 2016

Standard	Mean difference	Number of observations	T-statistic	P-value 1	P-value 2
3Y average growth	0.0027	472	0.2007	0.5795	0.4205
5Y average growth	-0.0497	433	-2.2124	0.0124	0.9863
LTG	-0.0422	244	-1.5463	0.0617	0.9383
Total Assets	-0.0615	271	-2.2241	0.0135	0.9865
Market Cap.	0.0056	251	0.2198	0.5869	0.4131
Leverage	-0.0399	339	-1.6828	0.0467	0.9533
Net Profit Margin	-0.0238	478	-1.0198	0.1544	0.8590
ROA	-0.0345	474	-2.0741	0.0193	0.9807
ROE	-0.0156	470	-1.0755	0.1413	0.8587
ROIC	-0.0330	479	-2.7137	0.0037	0.9966

Table 3 The Paired T-test of the Prediction Errors 2017

Standard	Mean difference	Number of observations	T-statistic	P-value 1	P-value 2
3Y average growth	-0.0408	463	-2.8005	0.0027	0.9973
5Y average growth	-0.0223	431	-1.4981	0.0674	0.9326
LTG	-0.0133	144	-0.4980	0.3096	0.6904

Total Assets	-0.0903	270	-3.0083	0.0014	0.9986
Market Cap.	-0.0680	261	-2.2953	0.0113	0.9887
Leverage	-0.0641	358	-3.3050	0.0005	0.9995
Net Profit Margin	-0.0443	470	-2.8522	0.0023	0.9977
ROA	-0.0334	463	-2.2915	0.0112	0.9888
ROE	-0.0419	455	-2.0975	0.0183	0.9817
ROIC	-0.0625	482	-2.9240	0.0018	0.9982

Table 4 The Paired T-test of the Prediction Errors 2018

Standard	Mean difference	Number of observations	T-statistic	P-value 1	P-value 2
3Y average growth	0.0026	472	0.2004	0.5795	0.4205
5Y average growth	-0.0497	433	-2.2124	0.0137	0.9863
LTG	-0.0422	244	-1.5463	0.0617	0.9383
Total Assets	-0.0615	271	-2.2241	0.0135	0.9865
Market Cap.	-0.0066	251	0.2198	0.5869	0.4131
Leverage	-0.0399	339	-1.6828	0.0467	0.9533
Net Profit Margin	-0.0238	478	-1.0190	0.1544	0.8456
ROA	-0.0345	474	-2.0741	0.0193	0.9807
ROE	-0.0156	470	-1.0755	0.1213	0.8587
ROIC	-0.0320	493	-2.7137	0.0034	0.9966

Overall, one can see that adding an extra criterion other than the industry classification tends to significantly increase the prediction errors.

Two criteria are used to test whether the size of the company reduces the prediction errors, which are total assets and market capital. Contradictory to the common practice of using the industry and the company size as the standard for choosing comparables, the additional standard of size did not have a significant impact on improving the accuracy of the P/E ratio prediction. Moreover, after adding the size of total assets as a criterion for selecting comparables, the prediction error increased significantly at the five percent level for all three years.

Historical or long-term growth rates were not effective in reducing the prediction errors compared to the base method of using industry classification only. For the year 2016 and 2018, the five-year average growth rate significantly increased the mean prediction error at the five percent level. Similarly, the three-year average growth rate significantly increased the mean prediction error at the five percent level.

Adding the standard of leverage ratio turns out not to be effective in reducing the prediction errors as well, with the mean prediction errors significantly increasing at the five percent level for all three years.

The standards that distinguish companies in accordance with their productivity, which are net profit margin, ROA, ROE, and ROIC are tested for their significance in reducing the prediction errors. However, adding the additional criteria regarding the productivity did not outperform the base method of using industry classification only, and ROA and ROIC significantly increased the prediction errors at the five percent level for all three years. This result can imply that a company outperforming the average performance of the industry is more affected by the outlook of the industry it belongs to.

Overall, the tests show that none of the additional standards tested so far is as effective in grouping companies with similar P/E ratios as using the industry standard alone. On the one hand, the results may suggest that the added standards are not relevant in deciding the P/E ratios. On the other hand, the result may indicate that for sub-grouping companies with similar P/E ratios, a more complicated combination of selection standards is needed to explain smaller variations in P/E ratios. More criteria for choosing comparables reduces the number of comparables, and the median P/E ratio of comparables is more likely to be affected by outliers, which ends up making the result inaccurate.

The problem of the median P/E ratio being biased with additional criteria can also be caused by the small number of companies in the sample. With a larger pool of companies from which too many comparables are selected when using only the criterion of industry while there still is a sufficient amount of comparables after adding more criteria, the test results can be different from this paper.

Based on the test result in table 2, 3, and 4, the first hypothesis is not accepted.

4.2. Adjusting the P/E ratios

Following the approach of changing the selection criteria of comparables, the method of adjusting P/E ratios is tested. A brief summary of the paired t-tests is shown in the table 5, 6, and 7. The full description of the result is attached as Appendix D.

Table 5 Replacing Earnings of the P/E Ratio with Damodaran's FCF of the Year

Year	Mean difference	Number of observations	T-statistic	P-value 1	P-value 2
2016	-0.7757	307	-4.2966	0.0000	1.0000
2017	-1.2538	376	-5.5544	0.0000	1.0000
2018	-10.4009	377	-1.1827	0.1188	0.8812

Table 6 Replacing Earnings of the P/E Ratio with the Koller's FCF of the Year

Year	Mean difference	Number of observations	T-statistic	P-value 1	P-value 2
2016	-0.9581	211	-4.0974	0.0000	1.0000
2017	-1.7376	285	-3.1108	0.0010	0.9990
2018	-1.4700	302	-2.3696	0.0092	0.9908

Table 7 Replacing Earnings of the P/E Ratio with the 12-month Forward EPS

Year	Mean difference	Number of observations	T-statistic	P-value 1	P-value 2
2016	-0.1683	394	-0.9546	0.1702	0.8298
2017	0.0962	405	3.6536	0.9999	0.0001
2018	-0.1764	426	-1.0073	0.1572	0.8428

The test results show that replacing the earnings with either one of the FCFs calculated by two different methods tends to increase the mean prediction error. Besides, the mean differences were the lowest among all other methods so far.

This result can be due to the fact that free cash flows are generally used to estimate the enterprise value, which includes the value of equity and the value of liabilities. Therefore, FCF per stock can be more affected by liabilities or the size of the company than the net income (earnings) per stock, which as a result may cause more variances in the ratio in the same industry. Even if the estimated value of the stock can be derived from the FCF, the chances are higher for FCFs to be negative even when the net income or EBITA is positive. Therefore, using the FCFs to adjust the P/E ratio can be eminently complicated.

Replacing trailing earnings with the 12-month forward earnings from the P/E ratio significantly reduced the prediction error at the five percent level in 2017. However, the test revealed that the mean prediction errors are not significantly different from original values for the rest.

Based on the results in table 5-7, the second hypothesis is also rejected.

4.3. Predicting P/E ratio with the best-fit regression

In order to find the best-fit regression that best explains the cross-sectional differences of the P/E ratios, the R-squared, adjusted R-squared, AIC, and BIC are compared among different regression models. The results are displayed in the table 8, 9, and 10 for the year 2016, 2017, and 2018 respectively.

Table 8 R-squared and Information Criteria 2016

SIC	Change EPS(%)	12-month forward EPS	Total Assets	Market Cap.	12-month forward dividend yield	Net Profit Margin	ROA	ROE	ROIC	Leverage	LTG	3Y Average Growth	5Y Average Growth	R&D Expense	R2	R2 adj.	AIC	BIC
o															0.230	0.143	4812	5074
o	o														0.457	0.388	4130	4390
o		o													0.256	0.160	4296	4556
o	o		o												0.456	0.384	4120	4389
o	o			o											0.459	0.388	4130	4395
o	o				o										0.530	0.467	4023	4287
o	o				o	o									0.530	0.467	3961	4224
o	o				o		o								0.530	0.467	3975	4238
o	o				o			o							0.530	0.467	3974	4238
o	o				o				o						0.530	0.467	4017	4285
o	o				o	o				o					0.534	0.467	3825	4090
o	o				o	o				o	o				0.535	0.467	3826	4095
o	o				o	o				o		o			0.537	0.463	3571	3836

o	o				o	o				o			o		0.544	0.469	3417	3679
o	o				o	o				o			o	o	0.545	0.468	3419	3685

Table 9 R-squared and Information Criteria 2017

SIC	Change EPS(%)	12-month forward EPS	Total Assets	Market Cap.	12-month forward dividend yield	Net Profit Margin	ROA	ROE	ROIC	Leverage	LTG	3Y Average Growth	5Y Average Growth	R&D Expense	R2	R2 adj.	AIC	BIC
o															0.197	0.109	4867	5130
o	o														0.464	0.396	4193	4454
o		o													0.212	0.113	4400	4662
o	o		o												0.464	0.397	4187	4452
o	o			o											0.465	0.396	4195	4460
o	o				o										0.551	0.490	3936	4199
o	o				o	o									0.552	0.491	3875	4137
o	o				o		o								0.568	0.508	3877	4139
o	o				o			o							0.570	0.511	3874	4136
o	o				o				o						0.556	0.495	3914	4181
o	o				o			o		o					0.554	0.489	3778	4042
o	o				o			o		o	o				0.564	0.500	3768	4037
o	o				o			o		o	o	o			0.579	0.512	3581	3852
o	o				o			o		o	o		o		0.580	0.507	3325	3590
o	o				o			o		o	o		o	o	0.585	0.512	3322	3591

Table 10 R-squared and Information Criteria 2018

SIC	Change EPS(%)	12-month forward EPS	Total Assets	Market Cap.	12-month forward dividend yield	Net Profit Margin	ROA	ROE	ROIC	Leverage	LTG	3Y Average Growth	5Y Average Growth	R&D Expense	R2	R2 adj.	AIC	BIC
o															0.162	0.071	4694	4958
o	o														0.373	0.296	4148	4411
o		o													0.180	0.080	4295	4558
o	o		o												0.373	0.294	4143	4411
o	o			o											0.376	0.298	4147	4414
o	o				o										0.454	0.385	4000	4266
o	o				o	o									0.455	0.384	3927	4192
o	o				o		o								0.456	0.386	3953	4218
o	o				o			o							0.455	0.384	3954	4219
o	o				o				o						0.456	0.386	3994	4264

o	o	o	o	o					0.478	0.406	3775	4042
o	o	o	o	o	o				0.479	0.406	3776	4047
o	o	o	o	o		o			0.464	0.385	3604	3872
o	o	o	o	o			o		0.474	0.391	3389	3653
o	o	o	o	o			o	o	0.474	0.390	3391	3660

The three regression selection processes, using data sets from three different years, show consistent results to some extent.

Firstly, one can see that using the percentage change of the EPS in 12-months compared to the current EPS as an explanatory variable is more effective in decreasing AIC or BIC, rather than using the absolute value of 12-month forward EPS. Adding the percentage change of the EPS after 12-months as an explanatory variable drastically increased the R-squared from 23% to 45.7% in 2016, from 19.7% to 46.4% in 2017, and from 16.2% to 37.3% in 2018. Also, both AIC and BIC by more than 700 in 2016 and 2017, larger than adding the 12-month forward EPS as it is. This result can make sense if investors have a certain value for the P/E ratio of each industry in mind, and the stock prices are adjusted in accordance with the predicted future earnings. As changes in ratios are more related to the percentage change of the divisor, the percentage change of earnings is more directly related to cross-sectional differences of P/E ratios.

Secondly, the size of a company, whether measured by total assets or total market capital, has neglectable impact on the model improvement. For all three years, adding market capital to the regression function increased BIC. AIC decrease by less than 10 for the three years.

Thirdly, among the variables that are related to profitability, either the net profit margin or ROE reduces AIC and BIC the most, compared to the other two. For ROE, this is fairly intuitive as the stock price is likely to be related to the return compared to the equity size. As for the net profit margin, the result suggests that the percentage of the “current” revenue left after “current” expense is more important than the percentage of the revenue over the company size or investments accumulated in the past when it comes to P/E ratio decision.

In addition, adding the 12-month forward dividend yield or leverage increased the explanatory power of the regression model. Given that a higher dividend yield essentially results in higher return per stock, this is an expected result. As a higher ratio of debt means more interest payment and more risk of default, the leverage ratio can be relevant with the P/E ratio.

Furthermore, adding the five-year average growth rate was closer to the true model than adding the three-year average growth rate. Historical trends are considered by investors with the expectation that the trend will persist for the near future, and in that sense, using a longer term to get the average may give a better picture of the growth trend. However, adding long-term growth increased the information criteria, which implies that the growth rate of far future has no huge effect on the P/E ratio.

Last but not least, the R&D expense actually increased AIC and BIC. From this, it can be concluded that the actual amount of investments for future production is not considered to be as important as the actual profits a company can acquire from the investments.

The best-fit function was selected as P/E ratio against SIC (dummy), percentage change of EPS, 12-month forward dividend yield, net profit margin or ROE, leverage, and five-year average growth.

To detect multicollinearity, the VIF was calculated. The factor was 2.194 in 2016, 2.321 in 2017 and 1.902 in 2018, which were all below 4. The Pearson correlation coefficients are all below 0.4, which indicates a weak or no correlation among variables. Therefore, there is no serious concern that there can be a multicollinearity problem (Appendix E).

With the function selected as the best-fit, the new prediction errors for P/E ratios of the target companies were calculated as can be seen in table 11. The detailed description of the result is attached in the Appendix F. Due to lack of data for some variables used in the regression, not all companies' P/E ratios could be predicted.

Table 11 The Prediction Errors from the Prediction with Regressions and the Paired T-test

Year	Mean difference	Number of observations	T-statistic	P-value 1	P-value 2
2017 Q1	0.0789	472	3.5504	0.9998	0.0002
2018 Q1	0.0758	474	3.3475	0.9996	0.0004
2019 Q1	0.0818	413	2.4822	0.9933	0.0067

For all three years, using the best-fit regression to predict the P/E ratios four-month ahead reduced the prediction errors significantly at the five-percent level compared to the method of peer company selection based on industry. Using regressions makes it convenient to add more than one variable to the SIC code to see if the variables in combination add explanatory value to P/E ratio. Furthermore, compared to using just the median of the peer companies, regressions can better take into account the exact values of each variables to decide the P/E ratio.

This can infer that there are common standards that investors look at when deciding on the proper stock price and the proper P/E ratio and the weight they give on a per unit change of each standard is similar to one another. The coefficients for each explanatory variable in the regression function can change over time, but there can be a value that best explains the cross-sectional differences of the P/E ratio for a certain period of time.

This paper has shown that using regression function is effective in enhancing the prediction accuracy when predicting the P/E ratio after one yearly quarter. It is worthwhile to further investigate whether the estimated regression function is also effective in predicting the P/E ratio after longer than one quarter or if the result is consistent when using a larger sample or companies from other markets.

5. Conclusion

This paper aimed to help understanding the factors that affect P/E ratios and to find the best method for setting the P/E ratio benchmark.

The first method compared the P/E ratio of a target company with the median P/E ratio of the peer companies selected by different sets of standards. The absolute value of the percentage difference was called the prediction error, and the paired t-tests were carried out to see if the medians of the new prediction errors decreased after adding more selection standards for peer companies.

None of the additional standards were consistently significant in reducing the prediction errors compared to the peer company selection using the industry standard only throughout the three-year period.

In the second method, the P/E ratio was adjusted. Replacing the earnings of the P/E ratios with the 12-month forward earnings significantly improved the prediction accuracy in 2017, but overall, adjusting the P/E ratio did not outperform the median P/E ratio of comparables chosen from the same industry as the benchmark.

The performed tests, however, may not have been precise due to the small number of companies in the dataset. When using more than one standard for the selection of peer companies, the number of peer companies drastically decreased, and some target companies did not have any peer companies at all. This may cause the median of the peer companies to be affected by outliers, therefore influencing the prediction errors.

The last method that was tested was using the best-fit regression for the prediction. The established regression model outperformed the basis method of using the median of comparables for all three years, implying that a combination of multiple standards is needed for more accurate predictions.

This paper has shown that the conventional method of using the size of the companies on top of the industry classification for choosing comparables adds little value to the prediction accuracy. It is also notable that the expected percentage change of EPS is an important factor describing variances in P/E ratios. Furthermore, it is also suggested that the industry dummy variable, the expected percentage change of EPS, the 12-month forward dividend yield, the leverage ratio and the five-year average growth rate in combination best describes the cross-sectional differences of the P/E ratios.

Deeper understanding in P/E ratios will not only help setting better benchmarks for company valuations, but will also enhance the understanding of factors that derive value for companies, which can also provide guidelines for executive members.

Appendix A. The Paired T-test/Additional Standard (2016)

Table 1. Total Assets

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	267	0.4945	0.0349	0.5696	0.4259	0.5632
Error_SIC_TA	267	0.6021	0.0597	0.9755	0.4846	0.7197
diff.	267	-0.1076	0.0422	0.6894	-0.1907	-0.0245

	mean(diff) = mean(error_SIC - error_SIC_TA)		t = -2.5501
Ho:	mean(diff) = 0		d.f. = 266
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0057	Pr(|T| > |t|) = 0.0113	Pr(T > t) = 0.9943

Table 2. Market Capital

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	248	0.4896	0.0337	0.5301	0.4233	0.5559
Error_SIC_MV	248	0.6015	0.0466	0.7345	0.5096	0.6933
diff.	248	-0.1118	0.0331	0.5207	-0.1769	-0.0467

	mean(diff) = mean(error_SIC - error_SIC_MV)		t = -3.3821
Ho:	mean(diff) = 0		d.f. = 247
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0004	Pr(|T| > |t|) = 0.0008	Pr(T > t) = 0.9996

Table 3. Leverage

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	319	0.4517	0.0296	0.5281	0.3936	0.5099
Error_SIC_Leverage	319	0.5251	0.0376	0.6717	0.4511	0.5990
diff.	319	-0.0733	0.0231	0.4120	-0.1187	-0.0279

	mean(diff) = mean(error_SIC - error_SIC_Leverage)		t = -3.1786
Ho:	mean(diff) = 0		d.f. = 318
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0008	Pr(|T| > |t|) = 0.0016	Pr(T > t) = 0.9992

Table 4. Three-year Average Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	437	0.4771	0.0257	0.5373	0.4266	0.5276
Error_SIC_3y	437	0.5183	0.0294	0.6153	0.4605	0.5762
diff.	437	-0.0413	0.0191	0.3996	-0.0788	-0.0037

	mean(diff) = mean(error_SIC - error_SIC_3y)		t = -2.1585
Ho:	mean(diff) = 0		d.f. = 436
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0157	Pr(|T| > |t|) = 0.0314	Pr(T > t) = 0.9843

Table 5. Five-year Average Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	415	0.4737	0.0264	0.5381	0.4217	0.5256
Error_SIC_5y	415	0.5224	0.0303	0.6168	0.4629	0.5819
diff.	415	-0.0487	0.0180	0.3674	-0.0842	-0.0133

	mean(diff) = mean(error_SIC - error_SIC_5y)		t = -2.7013
Ho:	mean(diff) = 0		d.f. = 414
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0036	Pr(|T| > |t|) = 0.0072	Pr(T > t) = 0.9964

Table 6. Long-term Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	140	0.3473	0.0236	0.2787	0.3008	0.3939
Error_SIC_ltg	140	0.3876	0.0270	0.3193	0.3342	0.4409
diff.	140	-0.0403	0.0236	0.2797	-0.0870	0.0065

	mean(diff) = mean(error_SIC - error_SIC_ltg)		t = -1.7036
Ho:	mean(diff) = 0		d.f. = 139
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0453	Pr(|T| > |t|) = 0.0907	Pr(T > t) = 0.9547

Table 7. Net Profit Margin

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	457	0.4811	0.0244	0.5216	0.4331	0.5290
Error_SIC_npm	457	0.5354	0.0309	0.6602	0.4747	0.5961
diff.	457	-0.0543	0.0175	0.3742	-0.0887	-0.0199
	mean(diff) = mean(error_SIC - error_SIC_npm)					t = -3.1050
Ho:	mean(diff) = 0					d.f. = 456
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0010		Pr(|T| > |t|) = 0.0020		Pr(T > t) = 0.9990	

Table 8. ROA

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	456	0.4668	0.0243	0.5195	0.4190	0.5146
Error_SIC_ROA	456	0.5235	0.0320	0.6835	0.4606	0.5864
diff.	456	-0.0567	0.0194	0.4150	-0.0949	-0.0185
	mean(diff) = mean(error_SIC - error_SIC_ROA)					t = -2.9159
Ho:	mean(diff) = 0					d.f. = 455
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0019		Pr(|T| > |t|) = 0.0037		Pr(T > t) = 0.9981	

Table 9. ROE

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	447	0.4707	0.0250	0.5292	0.4215	0.5199
Error_SIC_ROE	447	0.5282	0.0307	0.6484	0.4680	0.5885
diff.	447	-0.0575	0.0202	0.4276	-0.0973	-0.0178
	mean(diff) = mean(error_SIC - error_SIC_ROE)					t = -2.8440
Ho:	mean(diff) = 0					d.f. = 446
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0023		Pr(|T| > |t|) = 0.0047		Pr(T > t) = 0.9977	

Table 10. ROIC

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	465	0.4639	0.0240	0.5175	0.4168	0.5111
Error_SIC_ROIC	465	0.5232	0.0276	0.5949	0.4690	0.5774
diff.	465	-0.0592	0.0145	0.3137	-0.0878	-0.0306
	mean(diff) = mean(error_SIC - error-SIC - error_SIC_ROIC)					t = -4.0717
Ho:	mean(diff) = 0					d.f. = 464
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0000		Pr(|T| > |t|) = 0.0001		Pr(T > t) = 1.0000	

Appendix B. The Paired T-test/Additional Standards (2017)

Table 1. Total Assets

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	279	0.4087	0.0239	0.3986	0.3617	0.4556
Error_SIC_TA	279	0.4989	0.0426	0.7121	0.4149	0.5828
diff.	279	-0.0902	0.0300	0.5009	-0.1492	-0.0312

mean(diff) = mean(error_SIC - error-SIC - error_SIC_TA) t = -3.0083

Ho: mean(diff) = 0 d.f. = 278

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0

Pr(T < t) = 0.0014 Pr(|T| > |t|) = 0.0029 Pr(T > t) = 0.9986

Table 2. Market Capital

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	261	0.4223	0.0239	0.3855	0.3753	0.4692
Error_SIC_MV	261	0.4893	0.0355	0.5728	0.4194	0.5591
diff.	261	-0.0670	0.0292	0.4716	-0.1245	-0.0095

mean(diff) = mean(error_SIC - error-SIC - error_SIC_MV) t = -2.2953

Ho: mean(diff) = 0 d.f. = 260

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0

Pr(T < t) = 0.0113 Pr(|T| > |t|) = 0.0225 Pr(T > t) = 0.9887

Table 3. Leverage

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	358	0.4469	0.0240	0.4544	0.3997	0.4941
Error_SIC_Leverage	358	0.5110	0.0315	0.5960	0.4490	0.5729
diff.	358	-0.0641	0.0194	0.3668	-0.1022	-0.0259

mean(diff) = mean(error_SIC - error-SIC - error_SIC_Leverage) t = -3.3050

Ho: mean(diff) = 0 d.f. = 357

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0

Pr(T < t) = 0.0005 Pr(|T| > |t|) = 0.0010 Pr(T > t) = 0.9995

Table 4. Three-year Average Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	463	0.4605	0.0226	0.4857	0.4162	0.5049
Error_SIC_3y	363	0.5014	0.0255	0.5490	0.4512	0.5515
diff.	463	-0.0408	0.0146	0.3138	-0.0695	-0.0122

mean(diff) = mean(error_SIC - error-SIC - error_SIC_3y) t = -2.8005

Ho: mean(diff) = 0 d.f. = 462

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.0027	Pr(|T| > |t|) = 0.0053	Pr(T > t) = 0.9973

Table 5. Five-year Average Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	431	0.4617	0.0226	0.4682	0.4173	0.5060
Error_SIC_5y	431	0.4840	0.0245	0.5093	0.4358	0.5322
diff.	431	-0.0223	0.0149	0.3095	-0.0516	0.0070

mean(diff) = mean(error_SIC - error-SIC - error_SIC_5y) t = -1.4981

Ho: mean(diff) = 0 d.f. = 430

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.0674	Pr(|T| > |t|) = 0.1348	Pr(T > t) = 0.9326

Table 6. Long-term Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	144	0.4151	0.0332	0.3983	0.3494	0.4807
Error_SIC_ltg	144	0.4283	0.0360	0.4318	0.3572	0.4994
diff.	144	-0.0133	0.0266	0.3195	-0.0659	0.0394

mean(diff) = mean(error_SIC - error-SIC - error_SIC_ltg) t = -0.4980

Ho: mean(diff) = 0 d.f. = 143

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.3096	Pr(|T| > |t|) = 0.6193	Pr(T > t) = 0.6904

Table 7. Net Profit Margin

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	470	0.4496	0.0228	0.4951	0.4047	0.4945
Error_SIC_npm	470	0.4937	0.0294	0.6366	0.4360	0.5514
diff.	470	-0.0442	0.0155	0.3357	-0.0746	-0.0137

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_npm)		t = -2.8522
Ho:	mean(diff) = 0		d.f. = 469
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0023	Pr(|T| > |t|) = 0.0045	Pr(T > t) = 0.9977

Table 8. ROA

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	463	0.4577	0.0235	0.5066	0.4114	0.5039
Error_SIC_ROA	463	0.4909	0.0276	0.5932	0.4368	0.5451
diff.	463	-0.0333	0.0145	0.3123	-0.0618	-0.0047

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_ROA)		t = -2.2915
Ho:	mean(diff) = 0		d.f. = 462
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0112	Pr(|T| > |t|) = 0.0224	Pr(T > t) = 0.9888

Table 9. ROE

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	455	0.4557	0.0227	0.4840	0.4111	0.5003
Error_SIC_ROE	455	0.4976	0.0308	0.6563	0.4371	0.5581
diff.	455	-0.0419	0.0200	0.4264	-0.0812	-0.0026

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_ROE)		t = -2.0972
Ho:	mean(diff) = 0		d.f. = 454
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0183	Pr(|T| > |t|) = 0.0365	Pr(T > t) = 0.9817

Table10. ROIC

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	482	0.4555	0.0213	0.4676	0.4136	0.4973
Error_SIC_ROIC	482	0.5179	0.0325	0.7137	0.4540	0.5817
diff.	482	-0.0624	0.0213	0.4686	-0.1044	-0.0205

mean(diff) = mean(error_SIC - error-SIC - error_SIC_ROIC) t = -2.9240

Ho: mean(diff) = 0 d.f. = 481

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.0018	Pr(|T| > |t|) = 0.0036	Pr(T > t) = 0.9982

Appendix C. The Paired T-test/Additional Standards (2018)

Table 1. Total Assets

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	271	0.5058	0.0312	0.5144	0.4443	0.5674
Error_SIC_TA	271	0.5673	0.0388	0.6393	0.4909	0.6438
diff.	271	-0.0615	0.0277	0.4552	-0.1159	-0.0071

mean(diff) = mean(error_SIC - error-SIC - error_SIC_TA) t = -2.2241

Ho: mean(diff) = 0 d.f. = 270

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.0135	Pr(|T| > |t|) = 0.0270	Pr(T > t) = 0.9865

Table 2. Market Capital

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	251	0.5140	0.0306	0.4848	0.4538	0.5743
Error_SIC_MV	251	0.5084	0.0341	0.5399	0.4413	0.5755
diff.	251	0.0056	0.0256	0.4049	-0.0447	0.0559

mean(diff) = mean(error_SIC - error-SIC - error_SIC_MV) t = 0.2198

Ho: mean(diff) = 0 d.f. = 250

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.5869	Pr(|T| > |t|) = 0.8262	Pr(T > t) = 0.4131

Table 3. Leverage

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	339	0.5337	0.0289	0.5326	0.4768	0.5906
Error_SIC_Leverage	339	0.5734	0.0329	0.6064	0.5087	0.6382
diff.	339	-0.0398	0.0236	0.4351	-0.0863	0.0067

mean(diff) = mean(error_SIC - error-SIC - error_SIC_Leverage) t = -1.6828

Ho: mean(diff) = 0 d.f. = 338

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.0467	Pr(|T| > |t|) = 0.0933	Pr(T > t) = 0.9533

Table 4. Three-year Average Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	472	0.5091	0.0248	0.5394	0.4603	0.5578
Error_SIC_3y	472	0.5065	0.0247	0.5375	0.4579	0.5551
diff.	472	0.0026	0.0128	0.2786	-0.0226	0.0278

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_3y)		t = 0.2007
Ho:	mean(diff) = 0		d.f. = 471
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.5795	Pr(|T| > |t|) = 0.8410	Pr(T > t) = 0.4205

Table 5. Five-year Average Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	433	0.5452	0.0272	0.5669	0.4916	0.5987
Error_SIC_5y	433	0.5849	0.0338	0.7025	0.5185	0.6512
diff.	433	-0.0397	0.0179	0.3734	-0.0750	-0.0044

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_5y)		t = -2.2124
Ho:	mean(diff) = 0		d.f. = 432
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0137	Pr(|T| > |t|) = 0.0275	Pr(T > t) = 0.9863

Table 6. Long-term Growth Rate

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	244	0.4594	0.0255	0.3982	0.4092	0.5096
Error_SIC_ltg	244	0.5016	0.0376	0.5875	0.4275	0.5757
diff.	244	-0.0422	0.0273	0.4264	-0.0960	0.0116

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_ltg)		t = -1.5463
Ho:	mean(diff) = 0		d.f. = 243
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0617	Pr(|T| > |t|) = 0.1233	Pr(T > t) = 0.9383

Table 7. Net Profit Margin

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	478	0.5187	0.0243	0.5316	0.4709	0.5665
Error_SIC_npm	478	0.5425	0.0321	0.7009	0.4795	0.6055
diff.	478	-0.0238	0.0234	0.5107	-0.0697	0.0221

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_npm)		t = -1.0190
Ho:	mean(diff) = 0		d.f. = 477
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.1544	Pr(|T| > |t|) = 0.3087	Pr(T > t) = 0.8456

Table 8. ROA

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	474	0.5050	0.0231	0.5021	0.4597	0.5503
Error_SIC_ROA	474	0.5394	0.0251	0.5476	0.4899	0.5888
diff.	474	-0.0344	0.0166	0.3609	-0.0670	-0.0018

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_ROA)		t = -2.0741
Ho:	mean(diff) = 0		d.f. = 473
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0193	Pr(|T| > |t|) = 0.0386	Pr(T > t) = 0.9807

Table 9. ROE

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	470	0.5111	0.0247	0.5361	0.4625	0.5597
Error_SIC_ROE	470	0.5265	0.0272	0.5890	0.4732	0.5799
diff.	470	-0.0155	0.0144	0.3120	-0.0438	0.0128

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_ROE)		t = -1.0755
Ho:	mean(diff) = 0		d.f. = 469
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.1413	Pr(|T| > |t|) = 0.2827	Pr(T > t) = 0.8587

Table10. ROIC

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	493	0.5167	0.0242	0.5365	0.4693	0.5642
Error_SIC_ROIC	493	0.5486	0.0256	0.5693	0.4982	0.5990
diff.	493	-0.0319	0.0118	0.2610	-0.0550	-0.0088

	mean(diff) = mean(error_SIC - error-SIC - error_SIC_ROIC)		t = -2.7137
Ho:	mean(diff) = 0		d.f. = 492
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.0034	Pr(|T| > |t|) = 0.0066	Pr(T > t) = 0.9966

Appendix D. The Paired T-test/Adjusting the P/E ratio

Table 1. Damodaran's FCF 2016

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	307	0.4686	0.0373	0.6542	0.3951	0.5421
Error_SIC_FCFE	307	1.2443	0.1847	3.2370	0.8808	1.6079
diff.	307	-0.7757	0.1805	3.1634	-1.1310	-0.4205
	mean(diff) = mean (error_SIC - error_SIC_FCFE)					t = -4.2966
Ho:	mean(diff) = 0					d.f. = 306
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0000		Pr(|T| > |t|) = 0.0000		Pr(T > t) = 1.0000	

Table 2. Damodaran's FCF 2017

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	376	0.4965	0.0288	0.5581	0.4399	0.5531
Error_SIC_FCFE	376	1.7503	0.2265	4.3913	1.3050	2.1956
diff.	376	-1.2538	0.2257	4.3770	-1.6976	-0.8099
	mean(diff) = mean (error_SIC - error_SIC_FCFE)					t = -5.5544
Ho:	mean(diff) = 0					d.f. = 375
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0000		Pr(|T| > |t|) = 0.0000		Pr(T > t) = 1.0000	

Table 3. Damodaran's FCF 2018

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	377	0.5696	0.0315	0.6122	0.5076	0.6316
Error_SIC_FCFE	377	10.9705	8.7949	170.7653	-6.3228	28.2638
diff.	377	-10.4009	8.7942	170.7517	-27.6928	6.8910
	mean(diff) = mean (error_SIC - error_SIC_FCFE)					t = -1.1827
Ho:	mean(diff) = 0					d.f. = 376
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.1188		Pr(|T| > |t|) = 0.2377		Pr(T > t) = 0.8812	

Table 4. Koller's FCF 2016

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	211	0.4583	0.0438	0.6368	0.3719	0.5447
Error_SIC_FCF	211	1.4164	0.2310	3.3558	0.9610	1.8718
diff.	211	-0.9581	0.2338	3.3966	-1.4191	-0.4971
	mean(diff) = mean(error_SIC - error_SIC_FCF)					t = -4.0974
Ho:	mean(diff) = 0					d.f. = 210
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0000		Pr(|T| > |t|) = 0.0001		Pr(T > t) = 1.0000	

Table 5. Koller's FCF 2017

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	285	0.4391	0.0277	0.4678	0.3847	0.4938
Error_SIC_FCF	285	2.1768	0.5581	9.4215	1.0783	3.2753
diff.	285	-1.7376	0.5586	9.4295	-2.8370	-0.6381
	mean(diff) = mean(error_SIC - error_SIC_FCF)					t = -3.1108
Ho:	mean(diff) = 0					d.f. = 284
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0010		Pr(|T| > |t|) = 0.0021		Pr(T > t) = 0.9990	

Table 6. Koller's FCF 2018

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	302	0.5194	0.0310	0.5381	0.4585	0.5804
Error_SIC_FCF	302	1.4700	0.6204	10.7806	0.7589	3.2200
diff.	302	-0.9581	0.2338	3.3966	-2.6908	-0.2492
	mean(diff) = mean(error_SIC - error_SIC_FCF)					t = -2.3696
Ho:	mean(diff) = 0					d.f. = 301
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.0092		Pr(|T| > |t|) = 0.0184		Pr(T > t) = 0.9908	

Table 7. 12-month Forward EPS 2016

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	394	0.4249	0.0253	0.5021	0.3752	0.4747
Error_SIC_FWDPE	394	0.5932	0.1769	3.5112	0.2454	0.9410
diff.	394	-0.1683	0.1763	3.4990	-0.5148	0.1783

	mean(diff) = mean(error_SIC - error_SIC_FWDPE)		t = -0.9546
Ho:	mean(diff) = 0		d.f. = 393
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.1702	Pr(|T| > |t|) = 0.3404	Pr(T > t) = 0.8928

Table 8. 12-month Forward EPS 2017

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	405	0.4564	0.0241	0.4858	0.4089	0.5039
Error_SIC_FWDPE	405	0.3602	0.0234	0.4703	0.3142	0.4061
diff.	405	0.0962	0.0263	0.5301	0.0445	0.1480

	mean(diff) = mean(error_SIC - error_SIC_FWDPE)		t = 3.6536
Ho:	mean(diff) = 0		d.f. = 404
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.9999	Pr(|T| > |t|) = 0.0003	Pr(T > t) = 0.0001

Table 9. 12-month Forward EPS 2018

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC	426	0.5073	0.0256	0.5079	0.4570	0.5576
Error_SIC_FWDPE	426	0.6837	0.1740	3.5907	0.3417	1.0256
diff.	426	-0.1764	0.1751	3.6134	-0.5205	0.1678

	mean(diff) = mean(error_SIC - error_SIC_FWDPE)		t = -1.0073
Ho:	mean(diff) = 0		d.f. = 425
	Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
	Pr(T < t) = 0.1572	Pr(|T| > |t|) = 0.3143	Pr(T > t) = 0.8428

Appendix E. Pearson Correlation

Table 1. 2016

	Percentage Difference EPS	12-month Forward Dividend Yield	Net Profit Margin	Leverage	Five-year Average Growth Rate
Percentage Difference EPS	1.0000				
12-month Forward Dividend Yield	0.2847	1.0000			
Net Profit Margin	-0.1380	0.0571	1.0000		
Leverage	0.0543	0.1757	0.1129	1.0000	
Five-year Average Growth Rate	-0.0225	-0.0290	0.0468	-0.0004	1.0000

Table 2. 2017

	Percentage Difference EPS	12-month Forward Dividend Yield	ROE	Leverage	Five-year Average Growth Rate
Percentage Difference EPS	1.0000				
12-month Forward Dividend Yield	0.2530	1.0000			
ROE	0.0306	0.1442	1.0000		
Leverage	0.0872	0.2116	0.4093	1.0000	
Five-year Average Growth Rate	-0.0523	-0.0250	0.0505	-0.0113	1.0000

Table 3. 2018

	Percentage Difference EPS	12-month Forward Dividend Yield	Net Profit Margin	Leverage	Five-year Average Growth Rate
Percentage Difference EPS	1.0000				
12-month Forward Dividend Yield	0.2685	1.0000			
Net Profit Margin	0.0420	0.0653	1.0000		
Leverage	0.2022	0.2998	-0.0229	1.0000	
Five-year Average Growth Rate	-0.0115	-0.0517	-0.0549	-0.0176	1.0000

Appendix F. The Paired T-test/The Best-Fit Regression

Table 1. 2017Q1 Prediction Error

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC_2017	472	0.4852	0.0257	0.5578	0.4348	0.5357
Prediction_error	472	0.4063	0.0219	0.4760	0.3633	0.4494
diff.	472	0.0789	0.0222	0.4827	0.0352	0.1226
	mean(diff) = mean(error_SIC – prediction_error)					t = 3.5504
Ho:	mean(diff) = 0					d.f. = 471
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.9998		Pr(|T| > |t|) = 0.0004		Pr(T > t) = 0.0002	

Table 2. 2018Q1 Prediction Error

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC_2018	474	0.4794	0.0252	0.5484	0.4299	0.5289
Prediction_error	474	0.4036	0.0208	0.4539	0.3626	0.4446
diff.	474	0.0758	0.0226	0.4928	0.0313	0.1202
	mean(diff) = mean(error_SIC – prediction_error)					t = 3.3475
Ho:	mean(diff) = 0					d.f. = 473
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.9996		Pr(|T| > |t|) = 0.0009		Pr(T > t) = 0.0004	

Table 3. 2019Q1 Prediction Error

Paired T-Test

Variable	Observations	Mean	Standard Error	Standard Deviation	(95% Confidence Interval)	
Error_SIC_2019	413	0.5533	0.0734	1.4910	0.4091	0.6975
Prediction_error	413	0.4715	0.0538	1.0933	0.3658	0.5773
diff.	413	0.0818	0.0329	0.6696	0.0170	0.1465
	mean(diff) = mean(error_SIC – prediction_error)					t = 2.4822
Ho:	mean(diff) = 0					d.f. = 412
	Ha: mean(diff) < 0		Ha: mean(diff) != 0		Ha: mean(diff) > 0	
	Pr(T < t) = 0.9933		Pr(|T| > |t|) = 0.0135		Pr(T > t) = 0.0067	

References

Alford, A. W. (1992). The effect of the set of comparable firms on the accuracy of the price-earnings valuation method. *Journal of Accounting Research*, *30*(1), 94-108.

Bhojraj, S., & Lee, C. M. (2002). Who is my peer? A valuation-based approach to the selection of comparable firms. *Journal of accounting research*, *40*(2), 407-439.

Boatsman, J. R., & Baskin, E. F. (1981). Asset valuation with incomplete markets. *Accounting Review*, 38-53.

Bothra, A. & Williams, Z. (2019). *Multiple analysis: industry labels don't matter, performance does*. Retrieved from https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/multiples-analysis-industry-labels-dont-matter-performance-does

Damodaran, A. (2016). *Damodaran on valuation: security analysis for investment and corporate finance* (Vol. 324). John Wiley & Sons.

Dittmann, I., & Maug, E. G. (2008). Biases and error measures: How to compare valuation methods. *ERIM Report Series Reference No. ERS-2006-011-F&A*, 2006-07.

Goedhart, M., & Koller, T., & Wessels, D. (2005). The right role for multiples in valuation. Retrieved from https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/the-right-role-for-multiples-in-valuation#

Koller, T. & Goedhart, M. & Wessels, D. (2015). *Valuation: measuring and managing the value of companies* (6th edition). McKinsey & Company.

Kim, M., & Ritter, J. R. (1999). Valuing ipos. *Journal of financial economics*, *53*(3), 409-437.

Liu, C., & Ziebart, D. (1994). Explaining earnings quality} A market-based test of a simple measure of sustainable earnings. *Unpublished working paper. University of Illinois*.

Ohlson, J. A. (1990). A synthesis of security valuation theory and the role of dividends, cash flows, and earnings. *Contemporary accounting research*, *6*(2), 648-676.