TARGET PRICE ACCURACY OF FINANCIAL ANALYSTS' REPORTS

Abstract

This paper is a reiteration of the work carried out by Cavezzali, Rigoni, Nathan (2014). I examined the whole text of a wide sample of financial analysts' reports, in order to understand if different choices related to the valuation methods applied by the analysts affect the accuracy of the target prices. My findings show that the different kinds of valuation methods lead to similar levels of accuracy. Furthermore, I confute the corporate finance theory of hierarchy amongst valuation methods, illustrating that fundamental-based approaches don't implicate a superior capability to forecast target prices over market-multiple-based approaches.

My empirical evidence proves that a valuation made using a combination of different methods is equivalent to a valuation where only one method is applied.

Overall, this paper shows that the valuation methods, analyzed under several aspects, don't represent anyhow a relevant variable, in terms of target price accuracy.

Finally, the disclosure of the valuation methods used in the reports have a positive impact on the target price accuracy. Analysts who don't disclose any information related to the valuation procedure achieve systematically worse target prices.

1. Introduction

In line with the work of Cavezzali, Rigoni, Nathan (2014), I'm interested in analyzing the impact that different choices related to valuation methods have on target price accuracy.
In fact, there are several methods that financial analysts can use in order to carry out the valuation process, illustrated by corporate finance theory and professional practices. They are traditionally divided into two classes: those based on fundamentals of a company, such as cash flows, earnings and so forth, and those based on market multiples related to companies belonging to the same sector. The former have a forward-looking, multi-period nature and are supposed to be superior in terms of accuracy, since they are based on quantitative measures that are uniquely related to the individual performance of companies. Though, they are more expensive in terms of time and they are likely to present inputs errors, because of their looking-forward and complex nature.
On the other hand, the market-multiples approach, according to the theory, is less accurate because it is a relative and static valuation, which consists in comparing the trend of a company with respect to the trend of the sector it belongs to. The other side of the coin is that it's easily carried out and doesn't implicate a particular effort by the firm, which can find the data simply available in the market.

Financial analysts can discretionally choose among several existing valuation methods and this implicates the fact that they can represent a competitive advantage and a potential key of observation for the different levels of accuracy.
In fact, target prices can be achieved using only one valuation method, or a combination of different methods, in order to involve a wider base of elements. It can also be the result of the application of a main method, complemented with others which are subordinated to the main one; or it can be the result of the average, simple or weighted, of multiple different methods.

I found that fundamental-based and market-multiple-based approaches lead to similar levels of target price accuracy. Also, among the different categories of valuation methods, no one presents a superiority in forecasting target prices, whether they are used as primary proxies of the valuation or they are just present in the valuation procedure.

Differently from the findings obtained by Cavezzali, Rigoni, Nathan (2014), I also observed that a valuation model built combining different valuation methods bring similar results as the application of one single method, in terms of target price accuracy.

Overall, my results are in contrast with the corporate finance theory dictations, according to which the valuation process should be based on fundamental-based methods and, whenever possible, should be carried out simultaneously checking with different valuation methods.

Interestingly, on the other hand, my research brings evidence that the target price accuracy is positively correlated to the disclosure of the valuation methods used in the reports.
Target prices are systematically more accurate when the valuation methods used are disclosed.
My interpretation is that analysts make explicit the valuation methods whenever they make a more rigorous valuation procedure and, therefore, obtain a more accurate target price. Oppositely, hiding the valuation procedure could be a tool to justify, for instance, a price decided a priori by the broker and not supported by any of the valuation techniques.

Another interesting result I obtained is that the accuracy of earnings forecasts is unrelated to the target price accuracy. Though, my paper, together with prior researches (Bradshaw (2006), Bonini, Zanetti, Bianchini (2006)), has illustrated that analysts show differential abilities to forecast earnings.
The explanation given to this lack of correlation, proposed by the same researchers, is that the report activity may be used strategically by issuing firms to artificially drive market prices. According to this theory, analysts could try to exploit the stock price effect, associated with the release of new information, to rebalance their own portfolios or transfer risk from more informed to less informed investors, by appropriate trading strategies.
My work shows that both earnings forecasts and valuation methodologies are highly differentiated across single analysts. Though, these variables

show no impact at all on the target price accuracy. Therefore, a possible interpretation of the results from this research can be used as additional proof to the above-mentioned theory.
On the other hand, the other possible interpretation is that financial analysts present, overall, low skills in forecasting target prices, regardless of the valuation methods adopted, or the inputs they use, since the stock price is influenced by external factors such as the economy momentum, which are hard to predict or quantify.

The paper is organized as follows: Section 2 discusses the observations brought forward by prior literature; Section 3 describes the sample and the relevant data taken into account by this study; Section 4 illustrates the research methodology; Section 5 and 6 report the empirical results, together with their interpretation; Section 7 presents the conclusions of the paper.

2. Prior Literature

The previous literature related to the reports of sell-side analysts has mainly put the focus on the stock recommendations, the differential ability in forecasting earnings and the market reaction to these factors.
Only few have moved their attention to the ability of forecasting target prices.

As illustrated by Bonini, Zanetti, Bianchini, (2006), though, target prices forecasts provide a higher level of information quality to the market, since they should comprehend both earnings forecasts and stock recommendations. That's one reason why they should be the main subject of analysis around analysts' forecasting abilities.

Also, Brav and Lehavy (2003) and Asquith et al. (2005) showed that target prices bring new information to the market, independently from recommendations and earnings forecasts. For instance, Brav and Lehavy (2003) show that the market reaction to target prices is both unconditional and conditional on stock recommendations and earning forecast revisions. Similarly, Asquith et al. (2005) demonstrate that the market reacts to target price revisions regardless of earnings forecasts revisions.

As reported in their paper, also, Bradshaw, (2006), Bonini, Zanetti, Bianchini (2006) have proved that analysts show a different degree of forecasting abilities on earnings and stock recommendations.
Both Bonini, Zanetti, Bianchini (2006) and Bradshaw (2006) observed, though, that superior abilities of sell-side analysts to forecast earnings didn’t find a counterpart in a superior ability to forecast Target Prices.
Again, both Bonini et al. (2006), and Bradshaw (2006), suggest through their results that research activity may be used strategically by issuing firms to artificially drive market prices.

Once proved the relevance of the target prices with respect to the market, some have focused on the main drivers of their accuracy.
For what concerns the firm-related variables, Cavezzali, Rigoni, Nathan (2014), and Kerl and Walter (2008), found that volatility of a stock is negatively related to the target price accuracy.

Bonini, Zanetti, Bianchini (2006) also state that the company’s size is positively related to the target price accuracy. Similarly, Kerl and Walter’s (2008), and Cavezzali, Rigoni, Nathan (2014), show that analysts’ forecasts for stocks with a large market capitalization are more accurate.

Lastly, a few studies investigated how the methodologies used by analysts to achieve the target price, i.e. the valuation models, affects the accuracy of the forecast.

Bradshaw (2002), Demirakos et al. (2004) and Asquith et al. (2005) have shown that financial analysts prefer single-period earnings models, such as market multiples as they are easy to carry out.
On the other hand, Demirakos et al., (2004) illustrated that analysts adopt multi-period models to valuate companies characterized by high level of uncertainty due to their unstable earnings or a high growth rate.

Furthermore, Demirakos et al. (2010) compared the DCF and the price-to-earnings (PE) ratio approaches and found that the latter present a higher level of accuracy (69.88%) with respect to the DCF method (56.28%).
Conversely, Asquith et al. (2005) didn't find any significant correlation between valuation methods and target price accuracy.

Specifically, they fail to demonstrate the superiority of the DCF method with respect to other methods.

Finally, Cavezzali, Rigoni, Nathan (2014), focused their research on the impact of the valuation methods used by financial analysts, identified by reading the full text of a large sample of issued reports. They found that using a combination of different valuation methods among fundamental-based and market-multiple-based approaches brings better results as well, in terms of target price accuracy. They also observed that there isn't any significant variation in target price accuracy, though, when a fundamental-based approach, rather than a market-multiple-based approach is used as the main driver of valuation. This result is in contrast with the corporate finance theory of the hierarchy of fundamental-based valuation methods over market-multiple-based ones.

3. Sample and Relevant Data selection

Coherently with the purpose of my research, I had to collect the data related to the valuation methods used by sell-side analysts, in order to test if different choices on valuation practices affect the accuracy of target prices. Together with the information related to the valuation methods used by analysts, I also needed the data connected to the fundamentals of the companies of the sample, in order to build a more comprehensive analysis model, in line with previous researches.
To gather the data related to the firms, such as historical prices, market ratios, market capitalization, I used Reuters.

On the other hand, it was challenging collecting the information related to the valuation methods. In fact, in order to observe these variables, I needed to read the whole text of each report and code by hand their content, since these details are not available on financial commercial databases, which only reports synthetic elements of the reports, such as target price forecasts, earnings forecasts and analyst recommendations.

I examined the European Market in the financial year 2012, selecting, among the thousands available, 998 reports issued by 63 sell-side analysts related to the Companies which belonged to EuroStoxx 50 Index at the time.

I selected the reports which presented, at least, the information I considered of a minimum acceptable level and excluded from the analysis the ones which were too short or didn't contain any variables relevant to this research.

I picked up approximately 20 random reports for each one of the 50 companies across about 25 sectors. The period covered by the selected reports is the entire 2012 and the dates of issue are random as well.

Concerning the information contained in the reports, I could notice that, for the same company, sell-side financial analysts presented significant differences in carrying out their analysis. First of all, I could immediately notice that they show divergences in target prices forecasts, earnings forecasts and stock recommendations.

Similarly, it's easy to observe how they use different approaches in terms of degree of disclosure and valuation methodologies.
In fact, some analysts illustrate the valuation methods used to evaluate the company, while others produce synthetic reports with just Target price, recommendation and earnings forecasts.

Considering those analysts who give information related to the valuation methods used, it can be observed a wide set of methodologies, both in qualitative (whether fundamental-based approaches or market-multiples-based ones) and in quantitative terms.

Specifically, analysts subjectively choose which approach to be used in order to achieve their target price. The either use a main unique method alone or a main method followed by subordinated ones or even depict a target price as the result of an average, weighted or simple, of multiple valuation methods.

3.1 The valuation techniques

Before going forward, I shortly illustrate the differences that corporate finance theory currently proposes for valuation techniques.

The main differentiation among valuation methods, as already mentioned, is between fundamental-based approaches and market-multiple-based approaches.
The former have a looking-forward, multi-period nature and are supposed to be superior in terms of accuracy, since they are based on quantitative measures that are uniquely related to the individual performance of companies. Though, they are more expensive in terms of time and they are likely to present inputs errors, because of their complex nature.
In this category fall the cash-flow-based methods and the earnings-based methods. These valuation methodologies are used to assess the current value of a company, using its future earnings or cash-flows as main drivers, discounted to the individual level of risk attached to the company, which is its cost of capital and/or debt.

On the other hand, the market-multiple-based valuation methods are relative valuations that need the presence of an active market in order to be carried out. These methods compare the Price of a stock to some specific fundamentals of the company and in turn to the average performances of the sector the company belongs to. One advantage of this kind of methods is that they are easily carried out and don't demand a particular effort from the analysts, who can simply observe the data from the market.

According to the corporate finance theory, the fundamental-based approaches should lead to a superior accuracy of the evaluation process, since they are looking-forward, dynamic, multi-period approaches, which are also, most importantly, based on individual performances of the companies.
The market-multiples-based methods are, on the contrary, relative and static valuations.

In line with the differentiations proposed by the current theoretical frame-

-work, as Cavezzali, Rigoni, Nathan (2014), I identified the following five categories: net assets-based methods, cash flow-based methods, earnings-based methods, hybrid(blended) methods and market ratios methods.
In addition to the traditional methods, financial analysts use simplified methods, called heuristic methods, which are less time-consuming with respect to the traditional ones. I list the valuation methods observed in the reports, distinguished by category, comprehending both the traditional and the heuristic ones.

In the financial-based-methods category are comprehended: Discounted Cash Flow(DCF), Discounted Dividend Model(DDM), Gordon Growth Model(GGM), Adjusted Present Value(APV).
Among the income-based methods I could observe: Residual Income Model(RIM), Required Roe(RR).
The net-assets-based methods were Appraisal Value(AV), Embedded Value(EV), Net assets Value(NAV).
The only hybrid(blended) method I individuated is the Economic Value Added(EVA).
Lastly, the market-multiples approach comprehends all the possible relative valuations with respect to the market and to similar companies of the same sector.
Table 1 gives more information related to single valuation methods.

Table 1. Methods Classification

Method Category	Method technique
Net Assets Based Methods	Appraisal Value(AV), Embedded Value(EV).
Earnings-based Methods	Residual Income(RIM), Required Roe(RR).
Cash flows-based Methods	Dividend Discounted Model(DDM), Discounted Cash Flows(DCF), Gordon Growth Model(GGM), Adjusted Present Value(APV).
Blended Methods	Economic Value Added(EVA).
Market-Multiple Methods	Relative valuations to comparable companies.

Notes. The table synthesizes the different method classifications.

- **NAV-Based Methods**: These approaches take into account the company's underlying assets value net of the liabilities; usually this value is then divided by the outstanding shares in order to get the net asset per share. This kind of valuation approach is useful for those companies whose value come from the held assets rather than the stream of profit that was generated by the company business. The Embedded Value(EV) is usually computed as *EV=PVFP + ANAV*, where *PVFP* is the present value of future profits generated by the current business, *ANAV* the adjusted Net Asset Value. It represents the value of the "in force" business. The Appraisal Value can be obtained by adding the Value of the future New Business to the Embedded Value.
- **Earnings-Based Methods**: The Residual Income Model(RIM) considers the present value of the future streams of earnings of a company adjusted by its cost of equity. According to the Required Roe(RR), the value of the equity is computed as follows: E=(ROE/COE)* P/BV, where *ROE* is the return on equity, *COE* the cost of equity and *P/BV* is the Price-to-book-value ratio.
- **Cash flows-based Methods:** The cash flows-approaches use the present value of future cash-flows of a company, discounted by its cost of capital, in order to make the evaluation. Discounted Cash-Flows(DCF) use the Free Cash-flows to the firm as stream of cash flows; Dividend-discounted Models(DDM) considers the company dividends as cash flows. Gordon Growth Model(GGM) is a particular type of DDM, according to which the dividend growth rate is constant. The Adjusted Present Value(APV) evaluates a company, considering separately the value without the debt (Unlevered) and the value of the tax-shield and the expected cost of bankruptcy, eventually obtaining the Levered Value.
- **Blended Methods:** The Economic Value Added(EVA) is a method used to assess the value created by a company. It's computed as follows: EVA = NOPAT – WACC*Invested Capital, where *NOPAT* is the Net Operating Profit After Taxes, *WACC* is the Weighted Average Cost of Capital.
- **Market-Multiple Methods:** The market-ratio approaches evaluate a company by comparing specific fundamentals, usually earnings or cash-flows, to the same variables of comparable companies in the same sector.

4. Research Methodology
4.1 Research Hypotheses

In order to analyze the effect that different valuation methodologies have on the target price accuracy, I tested the veracity of the following hypotheses, reiterated from the work of Cavezzali, Rigoni, Nathan (2014).

"H1: The specific types of valuation method (DCF, DD, NAV and so on) used in the report overall have different impacts on target price accuracy."

"H2: At the macro category level, target prices resulting from fundamentals-based methods are more accurate than those derived from market multiple-based methods."

"H3: Target prices resulting from fundamentals-based "primary" methods are more accurate than those derived from market multiple-based "primary" methods."

I don't expect a superiority of the fundamental-based valuation methods over the multiple-based ones, in terms of target price accuracy. Though, I use the same hypotheses as the ones used by Cavezzali, Rigoni, Nathan (2014), to confirm that these hypotheses are biased, as they evidenced in their own work.
In fact, the results they obtained demonstrate that there is no substantial difference in the target price accuracy if a fundamental-based method is used over a multiple-based one.
Moreover, it is true that, according to the theory, using fundamental-based valuation methods should lead to a better target price accuracy than using market-multiples-based ones. Though, as stated by Damodaran (Investment Valuation, (2012)), due to their looking-forward nature, fundamental-based methods are characterized by a higher level of complexity in practice, increasing the potential for input errors.

"H4: Analysts who make explicit the valuation methods they use are more accurate than those who do not disclose them."

Again, Cavezzali, Rigoni, Nathan (2014) showed that analysts who give information about the valuation methods used don't present a greater target price accuracy in their reports. I expect to obtain coherent results.

In fact, disclosing this kind of information should be, in theory, unrelated to the precision with which the methods are used or the thoroughness of analysts' work.

"H5: Target prices derived from an average of different valuation methods are more accurate than those obtained with one primary method."

On the other hand, I expect this hypothesis to be true, in line with Cavezzali, Rigoni, Nathan (2014), but also with what suggest the corporate finance theory, according to which using a combination of different valuation methods should lead to a better valuation.

4.2 Variables Description

In order to test the above-listed hypotheses, I ran several linear regressions. I assumed the target price accuracy as the fixed dependent variable and considered, as independent variables, the alternative variables, respectively to the specific hypothesis taken in consideration.
In line with the previous research, together with the valuation methods-related variables, I included a group control variables, which are related to the fundamental characteristics of the firms.

In line with the work of Cavezzali, Rigoni, Nathan (2014) and De Vincentiis (2010), I used two alternative metrics for the target price accuracy.
The first one(FE1) is computed as:

$$FE1 = \begin{cases} \frac{TP - P\_max12m}{Pt}, & TP > Pt \\ \frac{TP - P\_min12m}{Pt}, & TP < Pt \end{cases} \tag{1}$$

where FE stands for forecast error, TP is the target price, P_max12m(P_min12m) is the maximum (minimum) market stock price registered in the 12 months following the report date and Pt is the current market stock price.

The second target price accuracy proxy (FE2), derived from Cavezzali, Rigoni, Nathan (2014), De Vincentiis (2010), Bonini et al. (2009), is:

$$FE2 = \left| \frac{TP - P_{+365}}{P_t} \right| \qquad (2)$$

where, again, TP is the target price, Pt is the current price and P(+365) is the market stock price registered 365 days after the issue date.
I discuss only the results related to FE1, since they are similar to those related to FE2.

I first investigate the effect of the type of valuation method used on the target price accuracy, in accordance with *H1*.
In order to test the first hypothesis, I take in consideration the distinction made in section 3, building five dummy variables. I analyzed the effect of the different valuation methods used, indicating M_FIN, M_INC, M_NAV, M_BLENDED, M_MULTIPLE, respectively referring to the correspondent class of method: financial, income, net-asset, hybrid and market multiples-based methods. Each variable gives the value of 1 if the method is present in the valuation process, 0 otherwise. They can all assume the value 1 at the same time, since the analysts can include all of the methods simultaneously in the valuation process

In order to test *H2* the focus must be put on the primary methods and on the further distinction between fundamental-based methods (financial, income-based, NAV) and market-multiple-based ones.
The dummy variable I used is *FUNDAMENTAL_MULTIPLE,* which gives 1 if the analyst uses a fundamental-based approach, 0 if market-multiple-based approach.

To test *H3,* I introduced the dummy variable *PRIMARY_NOPRIMARY,* which indicates the presence of a main valuation method. It gives the value of 1 if a main valuation method can be identified, 0 if the valuation is not driven by a method considered of a superior relevance to the others.
Subsequently, I identified the nature of the main method used, when present. Therefore, I introduced the same variables as the first indicated,

only related to the main methods. *MM_FIN, MM_INC, MM_NAV, MM_BLENDED, MM_MULTIPLE,* according to the class membership.

For what concerns the level of disclosure of the sell-side analysts, related to *H4,* I used the dummy variable *DISCLOSED_NOTDISCLOSED,* which gives the value of 1 if the analysts provide information about the methods used in the valuation process, 0 if the valuation methods used are not deductible from reading the report.
The work of Cavezzali, Rigoni, Nathan (2014) advanced the hypothesis that an analyst could exploit a non-disclosed report, in order to justify a target price decided ex-ante. Nevertheless, it's not difficult to give justifications to a target price decided a priori, even disclosing the valuation figures. Therefore, I don't expect a positive correlation between the transparency of the reports and the target price accuracy.

According to *H5,* a target price resultant from the application of different valuation methods should present a higher level of accuracy than a target price obtained using one single method. To test this hypothesis, I introduced *PRIMARY_MANY,* another dummy variable that gives the value of 1 if the valuation is the result of the combination of different methods, 0 if the process is carried out using one single method.

For what concerns the control variables, I first introduced the boldness of the target price (BOLDNESS). It's computed as the absolute value of the difference between the target price and the current stock price, scaled by the current stock price. In accordance with Cavezzali, Rigoni, Nathan (2014) and also Bonini (2010), I expect a negative correlation between the target price accuracy and the boldness of the target price. In fact, the larger the absolute difference between the target price and the current price, the more unlikely the target price will be met.

A second control variable is the volatility of the stock price, which is a sign of the predictability of the firm. It is computed as the standard deviation of the stock price in the year considered (2012) and the previous year (2011). In line with the option pricing theory, to a higher volatility of a stock, should correspond a higher target price accuracy. The results obtained by Bradshaw et al. (2013) and Cavezzali, Rigoni, Nathan (2014), though, show how the volatility is negatively correlated to the target price accuracy.

Another control variables taken into account is SIZE. It's the natural logarithm of the firm's market capitalization on the report date. I expect a positive correlation between target price accuracy and Size. This is due to the fact that larger companies show a higher maturity and stability in the market and consequently it is easier to predict for the financial analysts the future trend of such companies. Conversely, of course, smaller companies usually have lower portions of market share and their performances result less predictable.

A similar statement can be made for the control variable GROWTH, which indicates the growth rate of a company and it is represented by the price-to-book-value ratio. The growth rate refers to the company's degree of stability, with companies that grows at a slower pace being more predictable than those with greater growth opportunities. I, therefore, expect a negative correlation between GROWTH and target price accuracy.

Another control variable I introduced is the accuracy of earnings forecasts. The previous literature is split on the subject: according to the observations of Cavezzali, Rigoni, Nathan (2014) and Gleason et al. (2006), there is a positive correlation between the earnings forecast accuracy and the target price accuracy. The motivation to that is that more precise input (earnings forecasts) should lead to a more precise output (target price forecasts).

On the other hand, Bonini, Zanetti, Bianchini (2006) and Bradshaw (2006) observed that superior abilities of sell-side analysts to forecast earnings don’t find a counterpart in a superior ability to forecast Target Prices.

Therefore, I remain impartial about the results I expect from this variable.

To measure the accuracy of the earnings forecasts I used two methods proposed by the previous literature: the *Absolute Forecast Error(AFE)* and the *Proportional Mean Forecast Error(PMAFE)* measured as:

$$PMAFEij = \frac{AFEij - AAFEj}{AAFEj}(-1) \tag{3}$$

where AFE_{ij} is the earnings absolute forecast error for analyst *i,* in relation to company *j, $AAFE_j$* is the average of *AFE* in relation to company *j*.

$$AFEij = \frac{ACTUALj - FORECASTij}{ACTUALj} \quad (4)$$

where $ACTUAL_j$ is the actual earnings of company *j,* while $FORECAST_{ij}$ is the earnings forecasts issued by analyst *i* for the company *j*.

I also include in the model one last control variable: *FORAGE*. It is a proxy for the forecast age and it's measured as the time interval, expressed in days, between the report issue date and the end of the fiscal year. In line with the previous literature, I expect a negative impact of this variable on the target price accuracy.

Table 2 summarizes the definitions related to the variables used in the model.

Insert Table 2

5. Empirical Result
5.1 Descriptive analysis

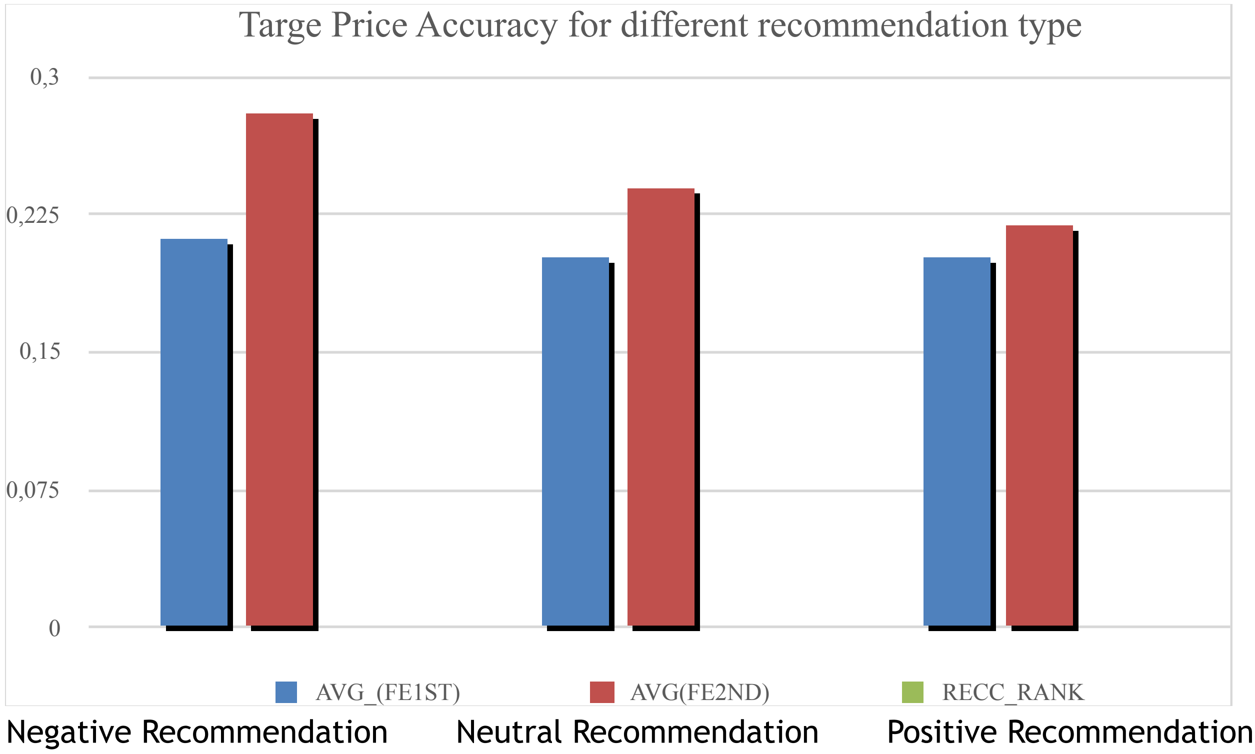
Table 3 reports the main descriptive statistics related to financial analysts' target price accuracy, differentiated by recommendation type (Panel A, Figure 1) and valuation methods characteristics (Panel B to F).

Table 3. Descriptive Statistics on target price accuracy

Descriptive Statistics on target price Accuracy-Overall data		
	FE1	**FE2**
No.	998	998
Mean	0.203	0.233
Std. Dev.	0.171	0.180
Median	0.162	0.199
Max	1.340	1.435
Min	0.001	0
Skewness	1.401	1.291
Kurtosis	5.897	5.977

Panel A. Descriptive Statistics on target price accuracy-by Recommendation type								
Rec. Type	**Positive Recommendation**		**Neutral Recommendation**		**Negative Recommendation**		**Total**	
	FE1	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**
No.	532	532	351	351	115	115	998	998
Mean	0.202	0.220	0.201	0.240	0.212	0.280	0.203	0.233
Std. Dev.	0.165	0.168	0.181	0.188	0.171	0.202	0.172	0.180
Median	0.167	0.183	0.143	0.207	0.172	0.246	0.162	0.199
Max	0.844	1.078	1.340	1.435	0.758	0.831	1.340	1.435
Min	0.001	0.0007	0.001	0	0.005	0.002	0.001	0
Skewness	1.216	1.261	1.669	1.484	1.181	0.690	1.401	1.290
Kurtosis	4.505	5.282	7.802	7.811	3.927	2.750	5.897	5.977

Figure 1. Target Price Accuracy for different recommendation categories



The overall data show how the financial analysts commit, on average, a significant error (20% for FE1, 23% for FE2) in forecasting target prices.

Also, Panel A indicates a widespread optimism among analysts, who issued more than 50% positive recommendations and only around 10% negative ones; this panel also illustrates that the accuracy is very similar for different recommendation types.

Panel B. Descriptive Statistics on target price accuracy-by level of disclosure of the valuation method used						
	DISCLOSED_NOTDISCLOSED =0		DISCLOSED_NOTDISCLOSED =1		Total	
	FE1	FE2	FE1	FE2	FE1	FE2
No.	303	303	695	695	998	998
Mean	0.221	0.256	0.195	0.223	0.202	0.233
Std. Dev.	0.187	0.201	0.164	0.170	0.171	0.180
Median	0.168	0.214	0.157	0.191	0.162	0.199
Max	1.340	1.435	0.844	1.078	1.340	1.435
Min	0.003	0	0.001	0.0007	0.001	0
Skewness	1.583	1.362	1.243	1.168	1.401	1.29
Kurtosis	7.427	6.808	4.442	4.781	5.897	5.977

Descriptive Statistics on target price accuracy-by hierarchy of valuation methods						
	PRIMARY_MANY=0		PRIMARY_MANY=1		Total	
	FE1	FE2	FE1	FE2	FE1	FE2
No.	496	496	199	199	695	695
Mean	0.201	0.234	0.190	0.214	0.198	0.228
Std. Dev.	0.168	0.182	0.165	0.155	0.167	0.175
Median	0.168	0.203	0.136	0.178	0.150	0.197
Max	1.340	1.435	0.767	0.687	1.340	1.435
Min	0.001	0.0007	0.002	0	0.001	0
Skewness	1.540	1.430	1.122	0.792	1.427	1.328
Kurtosis	7.418	7.154	3.956	2.992	6.522	6.638

Panel B gives evidence that, apparently, analysts who disclose the valuation methods used presents a slightly better target price accuracy. Though, the difference doesn't seem relevant in absolute terms(<5%).
It’s also shown that there isn't a substantial difference in target price

accuracy between analysts who estimate target prices through the combination of different valuation methods and those who use just one method.

Panel C. Descriptive Statistics on target price accuracy-by hierarchy of valuation method						
	PRIMARY_NOPRIMARY=0		**PRIMARY_NOPRIMARY=1**		**Total**	
	FE1	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**
No.	140	140	556	556	696	696
Mean	0.197	0.227	0.198	0.230	0.198	0.228
Std. Dev.	0.175	0.156	0.165	0.179	0.167	0.175
Median	0.132	0.190	0.163	0.199	0.149	0.197
Max	0.767	0.687	1.340	1.435	1.339	1.435
Min	0.004	0	0.001	.0007	0.001	0
Skewness	1.174	0.852	1.503	1.402	1.429	1.331
Kurtosis	3.907	3.164	7.328	7.060	6.526	6.644

Similarly, on Panel C it's shown how, apparently, the use of a main method in the valuation procedure is totally unrelated to the target price accuracy.

Panel D. Descriptive Statistics on target price accuracy-by fundamental-based and multiple-based valuation methods						
	FUNDAMENTAL_MULTIPLE =0		**FUNDAMENTAL_MULTIPLE =1**		**Total**	
	FE1	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**
No.	357	357	337	337	694	694
Mean	0.189	0.223	0.208	0.235	0.199	0.229
Std. Dev.	0.172	0.187	0.162	0.162	0.167	0.175
Median	0.137	0.188	0.181	0.204	0.150	0.198
Max	1.339	1.435	0.770	0.844	1.340	1.435
Min	0.001	0.0007	0.003	0	0.001	0

Skewness	1.783	1.656	1.014	0.800	1.426	1.327
Kurtosis	8.770	8.355	3.827	3.297	6.523	6.637

On Panel D are reported the descriptives related to the use of fundamental-based and market multiples-based valuation methods.
They both perform in a similar way in terms of target price accuracy.

Insert Panel E
Insert Panel F
Insert Panel G

Panels E to G focus on the relationship between the categories of valuation methods used, previously illustrated, and target price accuracy.
Apparently, according to those data, the Income-based method presents the highest accuracy among all. Though, a more rigorous process is needed to properly evaluate the differences in terms of accuracy among methods, since looking at the descriptive statistics can only give first impressions and hints related to the analysis.

On figure 2 it's shown the different level of accuracy among sectors. The graphic shows that the mean forecast error is ranged between 20% and 30%. The businesses related to banking and financial services seem to be the most difficult to predict while the most predictable are the Energy sector and the Retail one, with an average forecast error of approximately 10%.

Figure 2. Target price accuracy across sectors

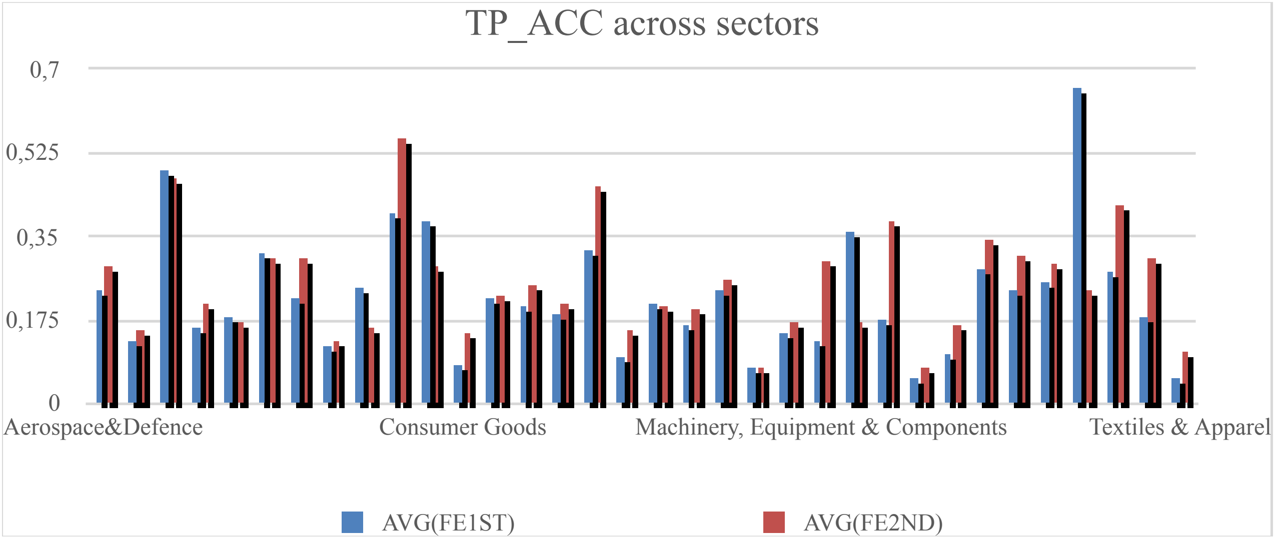


Table 4 and 5 report the main descriptive statistics related to the independent variables used in the regression model. They, respectively, illustrate the figures related to the control variables and those connected to the valuation methods used.

Table 4. Descriptive Statistics of the control variables						
	BOLDNESS	PMAFE	VOLATILTY	GROWTH	SIZE	FORAGE
No.	998	998	998	998	998	998
Mean	0.181	-0.058	5.083	1.42	10.340	284.479
Std. Dev.	0.161	0.576	4.617	2.35	0.626	71.91
Median	0.143	0.037	3.326	1.193	10.307	311
Max	1.612	1	21.676	9.738	11.713	365
Min	0	-3.011	0.135	-10.786	9.141	20
Skewness	2.055	-0.968	1.436	-1.757	0.075	-1.337
Kurtosis	11.389	6.157	5.125	17.949	2.138	4.226
p1	0.002	-1.881	0.135	-10.786	9.141	54
p25	0.066	-0.185	1.498	0.685	9.852	249
p50	0.143	0.037	3.326	1.194	10.307	311
p75	0.235	0.390	7.103	2.174	10.808	335

p95	0.509	1	14.77	4.929	11.360	356
p99	0.67	1	21.676	9.738	11.713	363

Table 5. Descriptive Statistics of the main independent variables of the model							
	DISCLOSED_NOTDISCLOSED	PRIMARY_NOPRIMARY	PRIMARY_MANY	FUNDAMENTAL_MULTIPLE	MM_FIN	MM_INC	MM_BLEN
No. (%=1)	695 69,63%	556 55,71%	199 19,93%	337 33,76%	291 29,16%	13 1,3%	2 0,2%
Mean	MM_NAV	MM_MULTIPLE	M_FIN	M_INC	M_NAV	M_BLEN	M_MULTIPLE
No. (%=1)	14 1,4%	306 30,66%	359 35,97%	32 3,2%	22 2,2%	4 0,4%	486 48,69%

Differently from the results obtained by Cavezzali, Rigoni, Nathan (2014), in over 69% of the reports of my sample, financial analysts disclose the valuation methods they used to obtain the target price.
Among these, 80% use a main method to carry out the valuation and more than 89% of them use a main method alone; only 11% check the valuation with secondary methods.

Overall, only around 28% (included both those who use a main method and those who don't) follow the suggestions of corporate finance theory, according to which the target price should be the resultant of different valuation methods.

Approximately 48% of the analysts involve a fundamental-based approach in the valuation process.
Financial and multiple-based methods dominate the scene, while income-based, NAV-based and blended methods are almost absent.
In fact, financial and multiple-based methods are overall used, respectively, around 51% and 81% of the times, while the others reach, together, only a 8% overall presence.
55% of the target prices are based on a market multiples-based Main method and nearly 42% on a financial-based Main one.

The last element of the descriptive analysis is the Spearman's correlation Matrix. No multicollinearity issues seem to be present.

Insert Table 6

5.2 The regression model.

In line with the work of Cavezzali, Rigoni, Nathan (2014), I test the previously listed hypotheses with proper linear regressions.
In order to test *H1* I ran the following regression:

$$ACCURACY = \alpha + \beta VALUATION\_METHODSj + \beta 2CONTROL\_VARIABLESj + \varepsilon j$$

(5)

where *j* is the single analyst, *VALUATION_METHODS* is the matrix of the five dummy variables listed above, representing the different valuation methods categories. Table 9 illustrates the results.

Table 9. The effect on the target price accuracy of different valuation methods

VARIABLES	(1) FE1	(2) FE1	(3) FE1	(4) FE1
BOLDNESS		0.1679214*** (0)	0.0928796** (0.026)	0.0989899** (0.017)
FORAGE		-0.0001481* (0.052)	-0.0001636* (0.064)	-0.0001482 (0.089)
PMAFE		-0.0093569 (0.317)	-0.0139083 (0.246)	
VOLATILITY		-0.0014347 (0.221)	-0.0019056 (0.173)	
GROWTH		0.0035233 (0.129)	0.0030929 (0.259)	
SIZE		-0.0273936*** (0.002)	-0.0277751*** (0.009)	-0.0264252** (0.011)
M_FIN	-0.0105168 (0.485)		-0.0088876 (0.561)	-0.0035762 (0.812)
M_INC	-0.0210079 (0.505)		-0.0368257 (0.242)	-0.0315957 (0.313)
M_NAV	0.0131237 (0.728)		0.0048389 (0.897)	0.0045911 (0.902)

M_BLENDED	-0.1095062 (0.200)		-0.0836523 (0.324)	-0.086348 (0.308)
M_MULTIPLE	-0.0117523 (0.475)		-0.0153666 (0.348)	-0.0134334 (0.410)
Constant	0.2128588***	0.5005998***	0.5393211***	0.5088862***
Observations	696	998	696	696
R-squared	0.0046	0.0450	0.0353	0.0095

***p<0,01 **p<0,05 p<0,1*

None of the valuation methods investigated shows a significant correlation with the target price accuracy (Columns (1), (3), (4)).
For what concerns the control variables, *GROWTH, VOLATILITY, FORAGE* and *PMAFE* are insignificant as well, while *BOLDNESS,* and *SIZE* are significant in the regression model (Column (2),(3),(4)). Respectively, and as expected, Boldness is negatively correlated to the target price accuracy, while Size shows a positive impact on it.

In order to test *H2,* I used the dummy variable *FUNDAMENTAL_MULTIPLE* previously illustrated, in the following regression:

$$\boldsymbol{ACCURACY = \alpha + \beta FUNDAMENTAL\_MULTIPLEj + \beta 2CONTROL\_VARIABLESj + \varepsilon j}$$

(6)

By aggregating the valuation methods into two macro-categories, distinguishing the fundamental-based methods from the multiple-based ones, the regression should better capture, if present, the differential effects of the theoretically superior fundamental-based approach on the target price accuracy. Table 10 reports the result of the regression.

Table 10. The effect on the target price accuracy of the fundamental and relative valuation methods

VARIABLES	(1) FE1	(2) FE1	(3) FE1	(4) FE1
BOLDNESS		0.1679214*** (0)	0.0894394** (0.032)	0.0945088** (0.022)
FORAGE		-0.0001481* (0.052)	-0.0001733* (0.050)	-0.00016* (0.066)
PMAFE		-0.0093569 (0.317)	-0.0129132 (0.280)	
VOLATILITY		-0.0014347 (0.221)	-0.0015677 (0.256)	
GROWTH		0.0035233 (0.129)	0.0026617 (0.330)	
SIZE		-0.0273936*** (0.002)	-0.0279255*** (0.008)	-0.0263716** (0.010)
FUNDAMENTAL_MULTIPLE	0.0197502 (0.121)		0.0186058 (0.145)	0.0214874
Constant	0.1889131***	0.5005998***	0.517066***	0.489436***
Observations	696	998	696	696
R-squared	0.0035	0.0450	0.0338	0.0289

***p<0,01 **p<0,05 p<0,1*

As expected, though, coherently with the work of Cavezzali, Rigoni, Nathan (2014), the *FUNDAMENTAL_MULTIPLE* variable is insignificant. The control variables show results in line with the previous regression.

It seems that, according to my results, complex multi-period, looking-forward valuation methods are equivalent to static and relative multiple-based methods in terms of target price accuracy.

In order to test *H3* and to better verify the previous results related to the fundamental-based and multiple-based approaches, I focused the attention on the primary valuation methods. I ran, therefore, the following regression:

$$ACCURACY = \alpha + \beta PRIMARY\_VALUATION\_METHODSj + \beta 2CONTROL\_VARIABLESj + \varepsilon j$$

(7)

Where *PRIMARY_VALUATION_METHODS* is the matrix of the five dummy variables, indicating the specific category used as a main valuation method, similarly to equation (5).
Table 11 reports the findings.

Table 11. The effect on target price accuracy of different type of main valuation methods

VARIABLES	(1) FE1	(2) FE1	(3) FE1	(4) FE1
BOLDNESS		0.1679214*** (0)	0.0938779** (0.025)	0.0991521** (0.017)
FORAGE		-0.0001481* (0.052)	-0.0001529 (0.083)	-0.0001409 (0.105)
PMAFE		-0.0093569 (0.317)	-0.0127868 (0.287)	
VOLATILITY		-0.0014347 (0.221)	-0.0016049 (0.254)	
GROWTH		0.0035233 (0.129)	0.0030163 (0.270)	
SIZE		-0.0273936*** (0.002)	-0.0279182*** (0.008)	-0.0263361* (0.010)

MM_FIN	0.0023661 (0.895)		0.0058733 (0.742)	0.005132 (0.773)
MM_INC	-0.0363818 (0.454)		-0.0432469 (0.372)	-0.0490885 (0.309)
MM_NAV	0.0608245 (0.195)		0.0525239 (0.261)	0.0485295 (0.298)
MM_BLENDED	-0.1516953 (0.204)		-0.1236954 (0.297)	-0.1333696 (0.260)
MM_MULTIPLE	0.0000269 (0.999)		0.0011389 (0.947)	-0.0035942 (0.830)
Constant	0.1971831***	0.5005998***	0.5164996***	0.4931557***
Observations	696	998	696	696
R-squared	0.0059	0.0450	0.0354	0.0301

***p<0,01 **p<0,05 p<0,1*

Again, also these variables are insignificant to the regression model, while the control variables behave on the same way as the prior regressions.

Differently from the work of Cavezzali, Rigoni, Nathan (2014), NAV doesn't result as the worst performing valuation method. It's also true, though, that in my sample NAV-based methods represent a scarce 2% of the observations.
It seems to be confirmed the equivalence between the fundamental-based valuation methods and the multiple-based ones: they are all irrelevant in terms of target price accuracy.

For what concerns the relevance of the disclosure of the valuation methods, testing *H4,* I ran the following regression:

$$\boldsymbol{ACCURACY = \alpha + \beta DISCLOSED\_NOTDISCLOSEDj + \beta 2CONTROL\_VARIABLESj + \varepsilon j}$$

(8)

where *DISCLOSED_NOTDISCLOSED,* as illustrated before, indicates whether the financial analyst disclose the valuation methods used in the report. Table 7 reports the results of the regression.

Table 7. REGRESSION MODEL- The effect on the target price accuracy of the valuation methods disclosure

VARIABLES	(1) FE1	(2) FE1	(3) FE1	(4) FE1
BOLDNESS		0.1679214*** (0)	0.1618753*** (0)	0.1645812*** (0)
FORAGE		-0.0001481* (0.052)	-0.00016** (0.036)	-0.0001464* (0.052)
PMAFE		-0.0093569 (0.317)	-0.009281 (0.320)	
VOLATILITY		-0.0014347 (0.221)	-0.0013482 (0.249)	
GROWTH		0.0035233 (0.129)	0.0033889 (0.144)	
SIZE		-0.0273936*** (0.002)	-0.0271241*** (0.002)	-0.025246*** (0.003)
DISCLOSED_NOTDISCLOSED	-0.0266292** (0.024)		-0.0217951* (0.062)	-0.0229354* (0.050)
Constant	0.2213369***	0.5005998***	0.5172098***	0.4916483***
Observations	998	998	998	998
R-squared	0.0051	0.0450	0.0483	0.0440

***p<0,01 **p<0,05 p<0,1*

Conversely from expectations and also differently from the results obtained by Cavezzali, Rigoni, Nathan (2014), the variable *DISCLOSED_NOTDISCLOSED* is statistically significant in the model and positively correlated to the target price accuracy. Again, the control va-

-riables *BOLDNESS* and *SIZE* are significant in the model (at 1%) and, as in the previous regressions, show, respectively, a negative correlation and a positive impact on the target price accuracy.

Eventually, in line with the work of Cavezzali, Rigoni, Nathan (2014), I test *H5,* in order to investigate whether the target price shows a greater accuracy when it's the result of a combination of different valuation methods. I ran the following regression:

$$\boldsymbol{ACCURACY = \alpha + \beta PRIMARY\_MANYj + \beta 2CONTROL\_VARIABLESj + \varepsilon j}$$

(9)

Table 8 reports the results.

Table 8. The effect on the target price accuracy of using a combination of different methods

VARIABLES	(1) FE1	(2) FE1	(3) FE1	(4) FE1
BOLDNESS		0.1679214*** (0)	0.091564** (0.028)	0.0970172** (0.019)
FORAGE		-0.0001481* (0.052)	-0.0001584* (0.072)	-0.0001419 (0.102)
PMAFE		-0.0093569 (0.317)	-0.0134544 (0.261)	
VOLATILITY		-0.0014347 (0.221)	-0.0019645 (0.158)	
GROWTH		0.0035233 (0.129)	0.0030288 (0.266)	
SIZE		-0.0273936*** (0.002)	-0.0276804*** (0.008)	-0.0261433** (0.010)
PRIMARY_MANY	-0.0111897 (0.426)		-0.0142776 (0.313)	-0.0102101 (0.464)
Constant	0.2014441***	0.5005998***	0.5244159***	0.4946253***
Observations	696	998	696	696
R-squared	0.0009	0.0450	0.0316	0.0251

***p<0,01 **p<0,05 p<0,1*

The control variables are consistent with the prior indications, while the variable *PRIMARY_MANY* is statistically insignificant in the regression model.
This result is in discordance with the research of Cavezzali, Rigoni, Nathan (2014) and it shows that using a combination of different methods to carry out the valuation doesn't make any significant difference in terms of target price accuracy.

6. Discussion of the results

The control variables showed consistent results, common to all the regressions carried out.
The variables *PMAFE, VOLATILITY,* and *GROWTH* are insignificant in all the models, differently from what expected. The variable *FORAGE* presented a formal significance, but the correlation coefficient is negligible and the p-value is barely acceptable (<0,1), therefore is actually insignificant as well.
On the other hand, the variables *SIZE* and *BOLDNESS* are significant in every regression, showing a consistent interaction with the target price accuracy.

For what concerns the *PMAFE* variable, my results show how the disagreement on the subject is well-founded. In fact, my findings illustrate that, to a greater accuracy of earnings forecasts, doesn't correspond a higher accuracy of the target price forecasts.
These results are in line with the researches of Bonini, Zanetti, Bianchini (2006) and Bradshaw (2006), but in disagreement with the results obtained by Cavezzali, Rigoni, Nathan (2014) and Gleason et al. (2006).

As expected, *BOLDNESS* is negatively correlated to the target price accuracy. In fact, as expected, the higher the difference between the forecast price and the current price, the more unlikely the price will be met.

For what concerns the firms-related variables, the *VOLATILITY* and *GROWTH* variables didn't show the results I expected, being insignificant in all the models, while *SIZE* proved to have a positive and consistent correlation with the target price accuracy.

FORAGE, the variable related to the age of the forecast, is insignificant in all the regression models, in line with the findings of Cavezzali, Rigoni, Nathan (2014).

Focusing on the main independent variables of the research, according to my observations, the valuation methods don't affect anyhow the target price accuracy and are insignificant in every model proposed.

In fact, the equation (5) shows how methods belonging to the different proposed categories (financial-based, income-based, blended, NAV-based, market-multiple based) bring all similar results in terms of target price accuracy, as expected and in line with Cavezzali, Rigoni, Nathan (2014).
The regression (7) gives further evidences to the insignificance of the different valuation processes, proving that different methods used as primary proxies of the target price brings equivalent results, with regard to the accuracy.

A further investigation was made to evidence whether the fundamental-based approaches lead to more precise target prices than the market-multiple ones, through the regression (6).
Again, both fundamental-based and market-multiple-based methods are insignificant in the model, meaning that more complex and time-consuming methods, such as DCF, are equivalent to quick and relative valuations achieved through a market-multiple-based approach.
The findings are in line with Asquith et al. (2005) and Cavezzali, Rigoni, Nathan (2014). They also confirm the statements of Damodaran (2012), who criticized the myth according to which, the more quantitative the model, the better the valuation. In fact, he argues that the valuation may be quantitative, but the inputs leave plenty of room for subjective judgments. Also, in his opinion, in many valuations, the price gets set first and the valuation follows.

To complete the valuation methods-related analysis, the linear regression (8) indicates that a combination of different methods, over the use of one single method, isn't a better approach to obtain a more accurate target price.

This result is in discordance with the corporate finance theory and with the results obtained by Cavezzali, Rigoni, Nathan (2014).

Overall, these results suggest that the valuation methodologies carried out by sell-side analysts are irrelevant to the target price accuracy.
The only relevant finding I obtained is related to the level of disclosure of the methods used.
In fact, the equation (8) proves that analysts who disclose the valuation methods applied to estimate the target price obtain better results in terms of accuracy.
My interpretation is that financial analysts don't disclose their valuation methods when they make scarcer evaluations in terms of thoroughness and precision. It could even be possible that, as already mentioned, some target prices are decided a priori and analysts hide their biased valuations behind opacity.

7. Conclusions

This paper is a reiteration of the work of Cavezzali, Rigoni, Nathan (2014), who analyzed the full text of financial analysts' reports, in order to understand the impact that different valuation methods have on the target price accuracy.

Prior researches have already presented significant results related to the determinants of the target price accuracy, such as the earnings forecasts and the fundamentals related to the evaluated companies.

Only a few, though, have focused their attention on structural elements of a report, such as valuation methods.

Furthermore, those who analyzed these factors have obtained conflicting and inconclusive results, related to the techniques adopted by the analysts to carry out the valuation.

Also, some of the prior literature have hypothesized that issuing firms could strategically use the research activity to artificially drive market prices. In fact, it has also been proven that the target prices bring additional information to the market and that influence the decisions of the investors. Under these circumstances, financial analysts could exploit target prices to create artificial perceptions around a particular stock in order to rebalance their portfolio or to carry out risk-shifting strategies.

The results of this research can be interpreted as an additional proof of this theory.
In fact, it's shown how neither the use of different valuation methods nor the earnings forecasts accuracy, despite being both significantly differentiated across analysts, have different impacts on the target price accuracy.
This, in turn, leads to two interpretations: either that analysts, overall, decide the target price ex-ante and subsequently carry out the valuation, or that they have limited abilities to forecast target prices.

Concerning the differential performances of the valuation methods, my findings do not support the superiority of the multi-period valuation models, promoted by corporate finance theory.

Another interesting result of my research is that financial analysts who disclose the valuation techniques used in their analyses are more reliable in terms of target price accuracy.

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Table 2. Summary of Variables Definitions

Variable Name	Description	Metrics
FE1	First proxy of forecast error	$FE1 = \begin{cases} \frac{TP-P\_max12m}{Pt}, & TP > Pt \\ \frac{TP-P\_min12m}{Pt}, & TP < Pt \end{cases}$
FE2	Second proxy of forecast error	$FE2 = \left\lvert \frac{TP - P_{+365}}{P_t} \right\rvert$
DISCLOSED_NOT DISCLOSED	It indicates those reports in which the valuation methods are disclose.	Dummy variable which assumes the value of 1 if the methods are disclosed, 0 otherwise.
PRIMARY_NOPRIMARY	It indicates the reports using a primary method.	Dummy variable which assumes the value of 1 if a primary method can be recognized in the report, 0 otherwise.
PRIMARY_MANY	It indicates the reports using a combination of different methods.	Dummy variable which assumes the value of 1 if the valuation is made using a combination of methods, 0 if only one method is used.
M_FIN, M_INC, M_NAV, M_BLENDED, M_MULTIPLE	Set of variables indicating the different category of valuation methods used in the report.	Set of dummy variables which represents the type of methods used in the valuation.(M_FIN=financial method, M_INC=income-based method; M_NAV=NAV-based method; M_BLENDED=Hybrid method; M_MULTIPLE=Market multiple-based method.) Each dummy is equal to 1 if the method is used in the valuation, 0 otherwise.
FUNDAMENTAL_MULTIPLE	It indicates the methods based on the fundamentals of the company and the methods based on the market multiples.	Dummy variable equal to 1 if the analysts use a fundamental-based approach to make the valuation, 0 if a market-multiple-based approach is used.

Variable Name	**Description**	**Metrics**
MM_FIN, MM_INC, MM_NAV, MM_BLENDED, MM_MULTIPLE	Set of variables indicating the different category of valuation methods used as Main Method in the report.	Set of dummy variables which represents the type of main methods used in the valuation. (MM_FIN=financial method, MM_INC=income-based method; MM_NAV=NAV-based method; MM_BLENDED=Hybrid method; MM_MULTIPLE=Market multiple-based method.) Each dummy is equal to 1 if the method is used as the primary method in the valuation, 0 otherwise.
BOLDNESS	Indicates the analyst boldness in forecasting the target price.	It's computed as the absolute value of the difference between the target price and the current stock price, scaled by the current stock price.
VOLATILITY	It indicates the price volatility	It is the standard deviation of the stock price in the year of reference.
SIZE	It indicates the company's size.	It's computed as the natural logarithm of the market capitalization of the company at the report issuing date.
GROWTH	It indicates the company's growth rate.	It is the price-to-book value ratio.
PMAFE	First proxy for earnings forecasts.	$PMAFEij = \frac{AFEij - AAFEj}{AAFEj}(-1)$
AFE	Second proxy for earnings forecasts.	$AFEij = \frac{ACTUALj - FORECASTij}{ACTUALj}$
FORAGE	It is a proxy for the forecast age.	It's computed as the the time interval, expressed in days, between the report date and the financial year end date.

Table 3.(Panel E-G) Descriptive statistics on target price accuracy

Panel E. Descriptive Statistics on target price accuracy-by type of valuation method																		
	M_FIN=0						M_FIN=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	337	0.200	0.175	0.150	1.339	0.001	359	0.196	0.160	0.150	0.770	0.002	696	0.198	0.167	0.150	1.340	0.001
FE2	337	0.228	0.190	0.1885	1.4356	0.0007	359	0.230	0.160	0.204	0.844	0	696	0.228	0.175	0.197	1.435	0
	M_INC=0						M_INC=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	664	0.200	0.170	.150	1.339	.001	32	0.177	0.131	0.164	0.454	.003	696	0.198	0.167	0.150	1.340	0.001
FE2	664	0.230	0.175	0.200	1.435	0	32	0.230	0.177	0.167	0.687	.0380	696	0.228	0.175	0.197	1.435	0

Descriptive Statistics on target price accuracy-by type of valuation method																		
	M_NAV=0						M_NAV=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	674	0.197	0.168	0.149	1.339	0.001	22	0.220	0.144	0.205	0.521	.0095	696	0.198	0.167	0.150	1.340	0.001
FE2	674	0.230	0.176	0.199	1.435	0	22	0.184	0.130	0.157	0.527	.0338	696	0.228	0.175	0.197	1.435	0
	M_BLENDED=0						M_BLENDED=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	692	0.199	0.167	0.150	1.339	0.001	4	0.082	0.061	0.059	0.172	0.037	696	0.198	0.167	0.150	1.340	0.001
FE2	692	0.228	0.175	0.197	1.435	0	4	0.287	0.174	0.270	0.493	0.114	696	0.228	0.175	0.197	1.435	0

Descriptive Statistics on target price accuracy-by type of valuation method																		
	M_MULTIPLE=0						M_MULTIPLE=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	210	0.202	0.150	0.180	0.770	0.003	486	0.196	0.175	0.144	1.339	.001	696	0.198	0.167	0.150	1.340	0.001

FE2	210	0.242	0.165	0.211	0.844	0.002	486	0.223	0.179	0.188	1.435	0	696	0.228	0.175	0.197	1.435	0

Panel F. Descriptive Statistics on target price accuracy-by type of valuation method

	MM_FIN=0						MM_FIN=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	477	0.197	0.175	0.144	1.339	0.001	219	0.200	0.148	0.178	0.770	0.003	696	0.198	0.167	0.150	1.339	.001
FE2	477	0.224	0.180	0.188	1.435	0	219	.238	0.165	0.209	0.844	0.002	696	0.228	0.175	0.197	1.435	0
	MM_INC=0						MM_INC=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	683	0.199	0.168	0.150	1.339	0.001	13	0.161	0.116	0.155	0.378	0.003	696	0.198	0.167	0.150	1.339	.001
FE2	683	0.230	0.176	0.199	1.435	0	13	0.178	0.100	0.143	0.362	0.038	696	0.228	0.175	0.197	1.435	0

Descriptive Statistics on target price accuracy-by type of valuation method

	MM_NAV=0						MM_NAV=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	682	0.197	0.167	0.150	1.339	0.001	14	0.258	0.148	0.230	0.521	0.062	696	0.198	0.167	0.150	1.339	0.001
FE2	682	2292	0.175	0.198	1.435	0	14	0.196	0.160	0.168	0.527	0.002	696	0.228	0.175	0.197	1.435	0
	MM_BLENDED=0						MM_BLENDED=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	694	0.198	0.167	0.150	1.339	.001	2	0.045	0.012	0.045	0.054	0.037	696	0.198	0.167	0.150	1.339	0.001
FE2	694	0.228	0.175	0.196	1.435	0	2	0.430	0.090	0.430	0.493	0.365	696	0.228	0.175	0.197	1.435	0

Descriptive Statistics on target price accuracy-by type of valuation method

	MM_MULTIPLE=0						MM_MULTIPLE=1						TOTAL		
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**
FE1	390	0.199	0.160	0.162	0.770	0.002	306	0.197	0.178	0.146	1.339	0.001	696	0.198	0.167
FE2	390	0.231	0.160	0.199	0.844	0	306	0.226	0.192	0.194	1.435	0.001	696	0.228	0.175

Panel G. Other descriptive Statistics on target price accuracy-by valuation methods features

	DISCLOSED_NOTDISCLOSED=0								**DISCLOSED_NOTDISCLOSED=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**

FE1	1.58	7.427	7.427	0.083	0.170	0.320	0.566	0.751	1.243	4.441	0.003	0.063	0.157	0.278	0.533	0.744
FE2	1.362	6.808	0.002	0.098	0.214	0.365	0.588	0.791	1.168	4.7809	0.003	0.087	0.191	0.316	0.544	0.731
	PRIMARY_NOPRIMARY=0								**PRIMARY_NOPRIMARY=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.1745	3.907	0.006	0.058	0.132	0.302	0.534	0.750	1.503	7.328	0.003	0.070	0.163	0.285	0.524	0.707
FE2	.8519	3.163	0.003	0.103	0.191	0.320	0.523	0.630	1.402	7.060	0.003	0.082	0.199	0.330	0.562	0.778
	PRIMARY_MANY=0								**PRIMARY_MANY=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.539	7.418	0.003	0.075	0.168	0.287	0.540	0.738	1.122	3.956	0.005	0.057	0.136	0.286	0.491	0.750
FE2	1.428	7.154	0.002	0.087	0.203	0.331	0.576	0.791	0.792	2.992	0.0025	0.081	0.178	0.320	0.502	0.630
	FUNDAMENTAL_MULTIPLE=0								**FUNDAMENTAL_MULTIPLE=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.783	8.770	0.003	0.059	0.137	0.279	0.540	0.738	1.014	3.827	0.006	0.08	0.181	0.298	0.522	0.728
FE2	1.6599	8.355	0.003	0.078	0.189	0.313	0.576	0.8	0.8	3.2979	0.003	0.104	0.204	0.335	0.527	0.688
	M_FIN=0								**M_FIN=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.636	8.125	0.003	0.061	0.150	0.290	0.550	0.740	1.1539	4.163	0.005	0.076	0.150	0.285	0.521	0.728
FE2	1.671	8.136	0.003	0.0804	0.189	0.322	0.604	0.791	0.750	3.223	0.0025	0.093	0.204	0.330	0.515	0.658
	M_INC=0								**M_INC=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.44	6.523	0.005	0.069	0.15	0.287	0.534	0.738	0.42	2.04	0.003	0.054	0.164	0.255	0.412	0.454
FE2	1.324	6.765	0.0025	0.082	0.199	0.328	0.544	0.738	1.469	4.1	0.038	0.114	0.167	0.271	0.630	0.688

Other descriptive Statistics on target price accuracy-by valuation methods features																
	M_NAV=0								**M_NAV=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.452	6.602	0.004	0.066	0.15	0.286	0.534	0.738	0.365	2.227	0.01	0.088	0.205	0.316	0.425	0.521
FE2	1.32	6.610	0.003	0.084	0.199	0.33	0.562	0.738	1.352	4.37	0.034	0.1	0.16	0.216	0.493	0.527
	M_BLENDED=0								**M_BLENDED=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.423	6.507	0.004	0.068	0.15	0.29	0.524	0.738	1.041	2.253	0.037	0.045	0.059	0.118	0.172	0.172
FE2	1.34	6.674	0.0025	0.085	0.197	0.327	0.558	0.738	0.195	1.396	0.114	0.145	0.270	0.423	0.493	0.493

	M_MULTIPLE=0								**M_MULTIPLE=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.069	4.14	0.006	0.093	0.18	0.285	0.521	0.661	1.524	6.987	0.004	0.059	0.145	0.29	0.540	0.75
FE2	0.82	3.438	0.0025	0.12	0.212	0.342	0.558	0.707	1.522	7.740	0.0025	0.079	0.188	0.321	0.551	0.551

	MM_FIN=0								**MM_FIN=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.5203	6.9366	0.003	0.059	0.144	0.29	0.55	0.75	1.0605	4.1527	0.007	0.084	0.178	0.285	0.504	0.661
FE2	1.5327	7.783	0.002	0.081	0.189	0.321	0.562	0.778	0.800	3.3835	0.004	0.0995	0.21	0.342	0.575	0.707
	MM_INC=0								**MM_INC=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.4274	6.4917	0.005	0.066	0.15	0.29	0.524	0.74	0.16	1.997	0.003	0.068	0.155	0.253	0.378	0.378
FE2	1.320	6.581	0.0025	0.084	0.2	0.328	0.558	0.74	0.44	2.175	0.038	0.121	0.143	0.255	0.362	0.362

Other descriptive Statistics on target price accuracy-by valuation methods features																
	MM_NAV=0								**MM_NAV=1**							
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.453	6.627	0.004	0.065	0.15	0.285	0.524	0.738	0.286	1.77	0.062	0.125	0.230	0.411	0.521	0.521

FE2	1.334	6.677	0.0025	0.086	0.198	0.328	0.557	0.738	0.95	2.931	0.002	0.099	0.168	0.252	0.527	0.527
			MM_BLENDED=0								**MM_BLENDED=1**					
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.426	6.522	0.0038	0.068	0.15	0.287	0.524	0.738	0	1	.0370	.0370	.0454	.0539	.0539	.0539
FE2	1.341	6.691	0.0025	0.086	0.196	0.325	0.557	0.738	0	1	0.365	0.365	0.429	0.493	0.493	0.493

Other descriptive Statistics on target price accuracy-by valuation methods features																
			MM_MULTIPLE=0								**MM_MULTIPLE=1**					
	Skewness	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**	**Skewness**	**Kurtosis**	**p1**	**p25**	**p50**	**p75**	**p95**	**p99**
FE1	1.085	4.019	0.005	0.076	0.162	0.286	0.504	0.7 27	1.719	8.328	0.004	0.057	0.146	0.284	0.567	0.738
FE2	.841	3.344	0.0025	0.100	0.199	0.327	0.529	0.6 88	1.679	8.408	0.003	0.076	0.194	0.328	0.576	0.791

6. The Spearman's correlation matrix

	Disclosed_not	TPACC1st	TPACC2nd	Size	Volatility	PMAFE	Growth	Boldness	Forage	Primary_no	MM_FIN	MM_INC
Disclosed_not	1											
TPACC1st	-0.099	1										
TPACC2nd	-0.099	0.502	1									
Size	-	-0.153	-0.082	1								
Volatility	-		-0.124		1							
PMAFE	-					1						
Growth	-			0.262	0.216		1					
Boldness	-		0.0802		-0.106		-0.217	1				
Forage	-			0.082		-0.114		-0.089	1			
Primary_no	0.069				0.167		0.078			1		
MM_FIN	-						0.178	-0.114		0.338	1	
MM_INC	-									0.069	-0.094	1
MM_BLENDED	-		0.068		0.065							
MM_NAV	-	0.0695		-0.085						0.072	-0.097	
MM_MULTIPLE	-				0.176		-0.093	0.0644		0.443	-0.596	-0.123
PRIMARY_MANY	-				-0.139					-0.783	-0.151	
Fundam_multiple	-	0.0832	0.066		-0.128		0.109			-0.167	0.692	0.143
m_fin	-			0.138	-0.109		0.167	-0.081		-0.377	0.653	-0.142
m_inc	0.073			-0.076	-0.082					-0.207	-0.146	0.639
m_nav	-			-0.121			-0.090	-0.066		-0.095	-0.123	
m_blended	-				0.073		0.066					
m_multiple	-		-0.075				-0.146	0.126		-0.28	-0.753	-0.164

	MM_BLENDED	MM_NAV	MM_MULT	PRIMARY_MANY	FUND_MULTIPLE	m_fin	m_inc	m_nav	m_blend	m_multiple
MM_BLENDED	1									
MM_NAV		1								
MM_MULTIPLE		-0.127	1							
PRIMARY_MANY		-0.068	-0.457	1						
FUND_MULTIPLE		0.148	-0.863	0.24	1					
m_fin		-0.127	-0.832	0.485	0.701	1				
m_inc			-0.192	0.173	0.181	-0.16	1			
m_nav		0.734	-0.161		0.154	-0.07		1		
m_blend	0.706		-0.068				0.168		1	
m_multiple	-0.082	-0.196	0.584	0.372	-0.677	-0.47		-0.18		1