“Financial statement analysis: a Trickle-Down benchmarked factor analytic approach”

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Abstract

This study discusses and demonstrates a lean modeling process that is used to identify a parsimonious set of information essential in Financial Statement Analysis (FSA) for decision making. Although FSA has been widely used to profile corporate financial performance, it is still a challenge for financial analysts (FA) to identify relevant profiling information in an effective and timely manner. The purpose of our lean modeling process is to: (1) reduce or eliminate the need for the "over-kill" checking where too many variables are needed to be collected; and (2) in addition to reduce possibly redundant financial variables, to identify the discriminating variables that discern firm performance. This modeling approach, which was developed from a long-term consulting engagement, was tested for "ease-of-use" and found to be simple to understand and produced consistent results. Finally, we use a real-world example to illustrate how financial analysts can apply our approach to develop benchmarks for making recommendations: Strong Buy, Buy, Hold, Sell and Strong Sell.

Keywords: factor variable reduction, discrimination testing, firm profiling.
JEL Classification: G11, G14, G17.

Introduction

In this study, we discuss and demonstrate a lean modeling process that we have used to identify a parsimonious set of information essential in Financial Statement Analysis (FSA) for decision making. The central construct in the lean modeling process is Factor Analysis. Such a study is needed because, although FSA has been widely used to profile corporate financial performance, it is still a challenge for financial analysts (FA) to identify relevant profiling information in an effective and timely manner (see Arnold et al., 2010; Epstein, 2007). For example, in the pre-Sarbanes-Oxley era, FA often had to collect numerous performance statistics to, as one of our friends in the investment banking industry used to say, "use as many firm profile points of reference as possible to shift through the 'creative accounting' to really understand what had gone on." From a pre-Sarbanes-Oxley era historical perspective this is a poignant comment that underscores the nervousness on the part of the FA that the information provided by the 10-K reports, even though duly certified, was suspect and hence resulted in the collection of many profiling variables to "triangulate" the information so as to adequately decipher the financial performance of the firm. The implementation of the Sarbanes-Oxley Act in recent years has fostered an environment that improves the reliability of financial statement information via more stringent regulations (see Lobo and Zhou, 2010). Because the FA may now rely more on a limited set of information for understanding the firm and its financial context in the current financial milieu, it is helpful for FA to have a lean modeling process in place to facilitate the FSA.

The purpose of our lean modeling process is two-fold. First, we demonstrate the process to reduce or eliminate the need for the "over-kill" checking where too many variables needed to be collected. Second, in addition to reduction of redundant financial variables, we discuss and showcase how to identify the discriminating key variables using a publicly available scoring system and then use these key variables as the benchmarks to evaluate firm performance and make the standard FAs' recommendation: Strong Buy, Buy, Hold, Sell or Strong Sell[1]. Although our process requires use of a publicly available firm scoring or rating system to help identify a parsimonious set of key variables as the benchmark, the derived recommendations do not seem to be contingent upon the selection of the scoring systems. To demonstrate this, we adopt two independent scor-

We wish to thank Mr. Nickolay Avramov, Financial Modeling Research Associate, FinAnalytica, LLP Sofia, Bulgaria for the fruitful discussions regarding this modeling process, the participants at the American University of Armenia in the course ACC510: Financial Statement Analysis Spring 2010 for their feedback on this FSA procedure, Professor Neuhauser of the Department of Finance, Lamar University, Beaumont Texas, USA, and the feedback given during the Research Interaction Forum II, for the 2011 American Accounting Association Annual Meeting, Denver CO, USA in particular Mr. Lucas A. Hoogduin, Senior Manager, KPMG, LLP.

[1] Such FA recommendations are often couched in other terminology such as Overweight, Over-Priced, Under-Valued, or Bargains to mention a few en vogue in the Investment Banking and Financial Consulting worlds. However, they all really are other nomenclature for Buy, Hold and Sell. Sometimes "Strong" is an adjective attached to the Buy or Sell recommendations. Although there is no "definition" for the meaning of this adjective that has been reported in the literature the usual meaning is: Strong Buy would suggest that a particular stock will almost certainly provide an excess return over the usual market index return for a reasonable period of time; Strong Sell would suggest that the market index will almost certainly provide an excess return over that of the stock for a reasonable period of time.

ing systems, identify one independent parsimonious set of key variables from each, and use each set of variables as benchmarks to make independent financial analysts' recommendations. We show that these two independent recommendations from our selected two scoring systems are not only robust, but also resemble the real-world recommendation made by the IB research firms, which speaks to the concomitant validity of our lean modeling process.

1. The Trickle-Down model (TDM): a lean financial statement analysis perspective

The essential features of the (TDM) are presented in Figure 1.

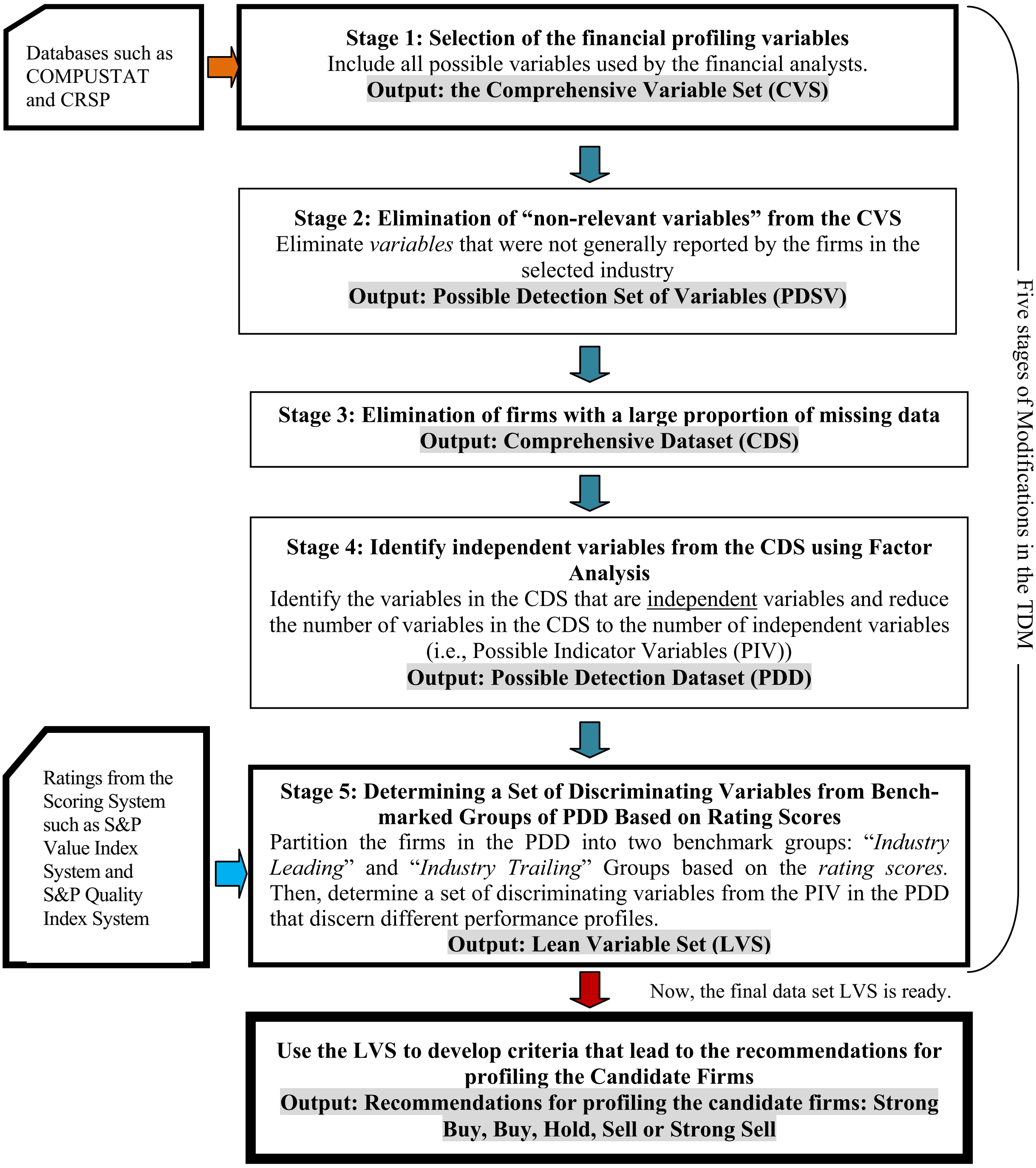

Fig. 1. Illustration for five stages of modifications in the TDM to prepare dataset for financial statement analysis

Figure 1 illustrates the overview of the five-stages of the TDM, which starts with a comprehensive or possible set of variables called the Comprehensive Variable Set (CVS). Then, after a series of variable reductions and firm consolidations applied to the CVS, the CVS will be reduced to a Lean Variable Set (LVS). Ultimately, the LVS will be used by the FA to benchmark the Candidate firms, i.e., those firms for which the FA will make a recommendation (Strong Buy to Strong Sell). The five stages of the aforementioned dataset modifications are now elaborated.

1.1. Stages of modifications in the TDM to prepare dataset for FSA.

Stage 1. Selection of the financial profiling variables for CVS.

The financial profiling variables are financial ratios and financial performance indicators that are commonly used in the literature or in practice to characterize firm performance. In order to construct a meaningful CVS, we suggest inclusion of "all" possible variables used by the FA. In other words, these variables could be selected from a variety of sources from any contemporary FSA textbook such as Fraser & Ormiston (2009) or alternatively from the experience of the FA. The idea is to include as many variables in the CVS as possible to ensure that the financial analysts will start the financial statement analysis with a rich set of variables to avoid selection bias while applying the TDM approach. Assume that the CVS has 21 possible variables.

Stage 2. Elimination of "Non-Relevant Variables" from the CVS.

At this stage, the FA will eliminate the variables that, due to the nature of the industry, do not pertain to characterize the firms in that particular NAICS or SIC grouping. For example, Fraser & Ormiston (2009) offer a number of variables including three profiling variables that are fundamentally involved with inventory:

1. Current ratio: (Curent assets / Current liabilities).
2. Days inventory held: (Inventory / Average daily sales).
3. Inventory turnover: (COGS/Inventory).

If it were the case that Inventory is **not** an important variable for the firms in the particular NAICS grouping, then the FA would eliminate from the analysis the three ratios: current ratio, days inventory held, and inventory turnover as they involve a variable that is not an impact variable for profiling firms in that particular NAICS. For example, in the software industry where there is little inventory it makes sense to eliminate these three inventory-related variables. We term this reduced variable set from the CVS the Possible Detection Set of Variables (PDSV). This is the set of variables that may be relevant to profiling of the candidate firms in that NAICS group which, we assume, had 155 firms. Therefore, after we reduce the CVS that had 21 variables down to 18 variables, the PDSV dataset will have the dimension of 155 firms on 18 variables whereas the CVS dataset had 155 firms on 21 variables.

Stage 3. Elimination of firms which have a large proportion of missing data.

Not all of the firms in a particular NAICS grouping have data uploaded or collected by the usual data sources such as COMPUSTAT. The FA should eliminate those firms in the PDSV dataset that have a large proportion of data in the not-reported category (i.e., missing data). This is an important step because a complete dataset with almost all data reported is required in the next stage where Factor Analysis will be applied. After elimination of such firms, the reduced PDSV will become the Comprehensive Dataset (CDS). Assume for purposes of explanation that 10 firms with a large proportion of missing data had been found, the CDS dataset after we delete 10 firms will have the dimension of 145 firms on 18 variables, down from the PDVS dataset of 155 firms on 18 variables.

Stage 4. Identify independent variables from the CDS using factor analysis.

At this stage, the FA needs to identify the variables in the set CDS that are independent variables and so reduce the number of variables in the CDS to the number of independent variables. This can be done by using a Standard Harman (1960) Factor Analysis on the set of firms in the CDS. This analysis requires a critically important data-preparation step, called Mahalanobis Screening, which will eliminate some, experience suggests about 15% of the firms in the CDS that, due to correlation-outliers, do not conform to the factor model assumption that the factors will be extracted from Pearson bi-variate space. This screening step will be presented in detail as part of the following illustrative example. Assume that the screening eliminated 17 firms from the CDS resulting in a dataset of 18 variables and 128 firms (145-17).

To illustrate how the Factory Analysis works at this stage, let us work with the numbers assumed above where we have 18 variables in the screened set CDS of 128 firms. After applying the Factor Model, assume that 18 variables loaded on five factors. In this case, one could select five variables – one from each factor. We will call these variables Possible Indicator Variables (PIV). Also assume that there were three variables in 18 variables that did not load on any of the five factors in a significant way. These three variables would also be selected as PIVs because, by definition, they are independent variables as they did not load on any of the five factors in a significant way. Therefore, in total there would be 8 variables (5+3) that one would classify as PIVs. In summary, the use of the Factor Analysis at this stage transforms the CDS into a new factor-adjusted dataset with only independent variables selected as the PIVs. We call this new-factor-adjusted dataset with 8 PIVs the Possible Detection Dataset (PDD) of 128 firms. In summary, the PDD has the dimension of 128 firms on 8 variables.

Stage 5. Determining a set of discriminating variables from benchmarked groups of PDD based on rating scores.

The goal of this stage is to determine a set of discriminating variables among the independent PIV in the PDD that will discern different performance profiles over the variables. To do so, we recommend that the FA partition the NAICS firms in the PDD into two benchmark groups: "Industry Leading" and "Industry Trailing" groups based on the rating scores given by an independent firm that publish ratings of organizations. One such firm, which we will use in our study, is Standard & Poors (S&P).

After partitioning the PIVs in the PDD into the "Industry Leading" and "Industry Trailing" groups, the FA will identify which independent PIVs in the PDD are statistically discriminating variables between the "Industry Leading" and "Industry Trailing" groups. We recommend conservatively setting the one-tailed alpha-detection level at less than 0.05 for the Median test for the observed relationship on an individual variable basis. The PIVs that are not discriminating will be further eliminated as they are not sensitive or discriminating variables. For instance, assume that among the 8 PIVs only 6 were discriminating in that these variables were the only six for which there was a statistically significant difference between the two groups: "Industry Leading" and "Industry Trailing" groups. Therefore, we will eliminate two statistically non-discriminating PIVs and the remaining six PIVs in this final variable set will be called the Lean Variable Set (LVS). LVS is the final dataset produced by the TDM. It has 6 variables and 128 firms and is a parsimonious set of variables that the FA may use to develop recommendations such as Strong Buy, Buy, Hold, Sell or Strong Sell.

We now present a detailed example as an illustration. This example serves as a convenient vehicle to illustrate the technical aspects of the five-staged TDM and how to use the ultimate result of the TDM – that is, the LVS.

1.2. A detailed illustrating example for TDM drawn from Semiconductors NAICS: 334413. In this example, we will present, in detail, the procedures needed to execute the TDM. The procedure of the TDM, as presented above, is normative in the sense that it is based upon parsimony through the Factor Model, i.e., the reduction of dataset to their independent essentials. This is the logical underpinning of Factor Analysis. However, the specific application of the TDM, of course, requires various parameters to be set: such as decisions as to factor rotations and statistical detection levels. Such parameters are idiosyncratic to the case under examination and so the application that we will present is heuristic and not normative.

1.2.1. Prelude – selection of our two candidate firms. We selected Semiconductors (NIACS: 443314) as this industry is a dynamic and powerful driving force in the global economy. From the firms in this industry, we selected two firms as the candidate firms for which we, the FA, will offer our recommendation: Strong Buy, Buy, Hold (i.e., Hold-off taking any action), Sell or Strong Sell. These two firms were selected after considering various investment banking industry reports. The first firm is Microchip Technology, Inc. (MCHP: NYSE); it was rated as positive by SIG: Susquehanna International Group, LLP (SIG). The second firm: NXP Semiconductor N.V. (NXPI: NYSE) was rated as Overweight by Morgan Stanley Research: North America. We intentionally selected these two firms with divergent profiles in order to facilitate our illustration of the detection sensitivity of the TDM.

1.2.2. The Five-staged TDM in details. We downloaded by EDT from WRDS™ all the firms in NAICS 334413 for which COMPUSTAT information existed for the latest year of record: 2009. This yielded 162 Firms excluding the two candidate firms.

Stage 1. Selection of the financial profiling variables for CVS.

We downloaded the data from COMPUSTAT and used that data to compute various variables which produced 31 Financial Performance Variables. These particular 31 variables were selected based on recommendation by Fraser & Ormiston (2009) (see Appendix A for the computational details of these 31 variables). These 31 variables and the 162 firms constitute our CVS, i.e., the initial dataset.

Stage 2. Elimination of "Non-Relevant Variables" from the CVS.

We did not eliminate any variables due to the "theoretic" inapplicability of a particular variable given the nature of the Semiconductor NAICS grouping, i.e., as we did above where inventory played no role in the firm's resources conversion process. However, we did eliminate variables that were not generally reported by the firms in the NAICS: 334413 group. This is a practical way to exclude variables compared to the theoretic inapplicability of a variable for the firms in a particular NAICS group. Our decision heuristic for eliminating variables from the CVS was as follows. If a variable has missing values for more than 30% of the 162 firms, this variable would not be a sufficiently rich profiling variable and should be eliminated. Thus, we eliminate the following five variables: Long-term Debt to Total Capitalization, Times Interest Earned, Cash Interest Coverage, Dividend Payout, and Dividend Yield. It is important to note that the elimination of these five variables in NAICS 334413 is based on the downloaded information from the COMPUSTAT for this specific industry. We do not imply that these variables are not valuable in other contexts.

After we deleted these five variables from the CVS, we obtained a reduced variable set of 26 variables – the PDSV. This is the set of variables that could pertain to profiling of the candidate firms in that NAICS group.

Stage 3. Elimination of firms which have a large proportion of missing data.

At this stage, the financial analysts should eliminate those firms in the PDSV that have a large proportion of missing data. Recall this is now the firm elimination stage. Similar to the decision heuristic we used for eliminating variables from the CVS in the Stage 2, we eliminated a firm if this firm contains five or more missing data points for variables in the PDSV. For the 162 firms there were nine such firms: 3DION, 3OPTI, 3MMTIF, 3NENE, VIRL, MOSY, 3CNUV, CSIQ and PSEM. After elimination of these firms, the reduced PDSV will become the CDS. In this case we now have the CDS including 153 firms on 26 variables where we started out with 162 firms on 31 variables.

Stage 4. Identify independent variables from the CDS using Factor Analysis.

The FA now need to identify the variables in the CDS that are independent variables and reduce 26 variables in the CDS to the number of independent variables. This can be done by using a Standard Harman (1960) Factor Analysis on the set of 153 firms in the current CDS. The analysis requires a critically important data-preparation step which will eliminate some of the firms in the CDS that do not conform to the factor model. The details of the data-preparation step are as follows: because the Factor Analytical Model uses correlation as the grouping metric, it is sensitive to outliers; thus it is recommended to take out any correlation outliers. This can be most simply done using the Mahalanobis Screen (Mahalanobis (1936)/JMP: SAS Version 9). The Mahalanobis Screen is programmed in SAS/JMP, v 9.0. (Sall, Creighton & Lehman, 2008). We used the usual 95% confidence interval as the screening criterion, i.e., any firm that had variable relationships that fell outside the 95% confidence interval for the 26-varaible correlation relationships was eliminated from the analysis as such an "outlier" firm may perturb the working of the Factor Model. This factors screening procedure resulted in 22 firms being eliminated as they had variables that represented correlation outliers: AMD, INVX, INTC, SMTC, LOGC, 3SLTZ, PANL, STKR, NMGC, 3SKYIQ, MTLK, ESLR, MSPD, TSRA, 0004B, 3SESI, HITT, ACTS, FSLR, 3SUNV, IRF and LLTC. Therefore, after we eliminated these 22 firms as a data-preparation step for Factor Analysis, we have 26 variables and 131 (153-22) firms left in the CDS ready to be inputted into Factor Analysis.

The result of Factor Analysis is a Factor Rotated Matrix from which we will select the PIVs (see Appendix B). All the details and data of the Factor Analysis can be found at Scholarly Commons (http://repository.upenn.edu/).

With the standard eigenvalue cut-off of 1.0 we identified eight factors for rotation. Using the standard variable factor loading cut off of .71 we identified the variables that grouped together on a particular factor. Then, we used our judgment as to which of the variables were to be selected as the characteristic variable for that factor. The rationale of our selection of the PIVs follows. In Appendix B, let us consider Factor 1 where the following six variables loaded significantly on this factor, i.e., the rotated loading was > 0.71 (with loading scores in boxes): ROA, Operating Profit Margin, Net Profit Margin, Cash Flow Margin, Cash Return on Assets, and EPS Increase (%). We selected ROA as the PIV because it has a clear definition, a demonstrated profiling acuity for evaluating firm performance, and contains Net Profit Margin in its calculation. For Factor 2 we selected the Quick Ratio rather than the Current Ratio for its simplicity, i.e., it does not have inventory in its definition. Inventory Turnover, A/R Turnover and Payable Turnover were selected from Factor 3, 4, and 5 as PIVs for they are the "flip-side" of Days Inventory Held, Average Collection Period, and Days Payable Outstanding. We selected Debt to Equity ratio as the PIV from Factor 6 because it has a clear definition and ideally is similar to the concept of Financial Leverage. Fixed Assets Turnover was selected from Factor 7 for it was the only variable with significant loading.

In summary, the following seven variables were selected to be the PIV (see Appendix B for the variables with numbers in the boxes highlighted in Bold): Quick Ratio, A/R Turnover, Inventory Turnover, Payables Turnover, Fixed Asset Turnover, Debt to Equity Ratio, and ROA. In addition to the above 7 factor-independent variables chosen directly from factors, there were 9 variables that did **not** load significantly on any of the rotated factor matrix; therefore, each of these nine variables was selected as PIVs since by definition they were independent variables. These nine non-associated variables (see Appendix B for the variables in Bold) are: Cash Flow Liquidity, Cash Conversion or Net Trade Cycle, Total Assets Turnover, Debt to Asset Ratio, ROE, Cash Flow Adequacy, Gross Profit Margin, PE Ratio, and Effective Tax rate.

The process of the Factor Analysis reduced the 26 variables to the 16 independent PIVs [i.e., 7 + 9] indicated above. The use of the Factor Analysis at this stage transforms the CDS into a new factor-adjusted dataset with only independent variables selected as the PIVs. We call this factor-adjusted dataset the PDD which now includes 131 firms and 16 PIV.

Stage 5. Determining a set of discriminating variables from benchmarked groups of PDD based on rating scores.

According to Figure 1, we are now entering the "benchmarking" stage. The goal of this stage is to determine a set of discriminating variables from the 16 independent PIV in the PDD that discern different performance profiles so as to develop benchmarking information. To identify the discriminating PIVs, we divided the NAICS firms in the PDD into two benchmark groups: "Industry Leading" and "Industry Trailing" groups based on their rating scores. Then, we compared the score values of the 16 independent PIVs between these two groups to identify discriminating PIVs that are critical in separating these two groups. Specifically, we selected two scoring indexes from Standard & Poors: Fair Value Scoring (http://www.allstocks.com/html/fair_value_s_p_futures_or_prem.html) and Quality Rating Index (http://www2.standardandpoors.com/spf/pdf/media/QualityRankingWhitePaperFinal.pdf).

The Fair Value Scoring is an Over- or Undervalued index calibrated with respect to returns on the S&P500. A score of 5 stands for the most Undervalued, a positive indication, while a score of 1 represents the most Overvalued, a negative indication. This index is a forward-looking or projection Index. According to Standard & Poors: "The model calculates a stock's weekly fair value, the price at which we believe an issue should trade at current market levels, based on fundamental data such as earnings growth potential, price-to-book value, return on equity and dividend yield relative to that of the S&P 500 index."

The second indexed that we used was the Quality Rating Index organized based upon a 10-year average of dividends and earnings with A+ representing the highest quality and C representing the lowest quality. In comparison to the Fair Value Index, the Quality Rating Index is a historical-relative index constructed with the past historical financial data.

We coded the 131 firms in the PDD by assigning to each of them the Value and Quality rating scores as downloaded from the S&P rating service. These two scores for each firm represent the independent scores from two different rating systems. Once the PDD was coded with two rating scores, we identified discriminating PIV to form a LVS from the 16 independent PIVs based on the scores of each rating system. Since we adopted two different rating scores, we will obtain two LVSs: one LVS for each rating system, respectively. These two LVSs were independent of each other and theoretically should lead to two independent conclusions as we, the FA, used each independent LVS to evaluate the candidate firms for making recommendations. See Mead (2011).

Now, we discuss the details of procedures used to identify the LVS and then use it to develop criteria for making financial analysts' recommendations for Fair Value Scoring (i.e., Scoring System #1) and Quality Rating Index (i.e., Scoring System #2), respectively.

2. Scoring system #1: Fair value system with undervalued, as a positive indication, and overvalued, as a negative indication

2.1. Step 1: Identification of the LVS based on the ratings of the scoring system #1. We began by classifying the 131 firms based upon their fair value scores into two groups. The "Industry Leading" group includes the Undervalued firms rated with Fair Value scores of 5 or 4. The "Industry Trailing" (i.e., Poor Performance) group contains the Overvalued firms rated with scores of 2 or 1. We eliminated the "Equal" Valued group rated with a score of 3 as we were interested in the discriminative power of the 16 variables in the PDD.

Any of the 16 variables in the PDD that fail to discriminate between the two groups were eliminated from the analysis. We set the discrimination criteria at a one-tailed p-value less than 0.05 for the Median test. Our test results (see Appendix C) showed that only the following 5 of the 16 independent PIVs in the PDD are discriminating variables for the Fair Value rating system.

2.1.1. ROA, ROE, PE Ratio, Total Assets Turnover, and Cash Conversion or Net Trade Cycle. These five variables constituted our first LVS with respect to the partition of two groups using the Fair Value rating scores (i.e., our Fair value or forward-looking Scoring System #1). These five variables represent a wide spectrum of aspects that draw the line between the Undervalued Group: "Industry Leading" and Overvalued Group: "Industry Trailing". Specifically, Total Assets Turnover represents the effectiveness of a firm to utilize assets for generating sales. ROA equals Net Profit Margin multiplied by the Total Assets Turnover, showing that in addition to Total Assets Turnover, the ability of firms to retain the generated sales for the bottom line – net income (i.e., Net Profit Margin) is valuable for firm valuation. Then, ROE equals to ROA multiplied by the ratio of Assets to Equity, implying that the financial leverage respecting the ratio of assets and equity is critical in determining the fair value of firms. The above three variables – Total Assets Turnover, ROA, and ROE taken together portray the income-generating characteristic of firms. Beyond the previous three income-generating variables, PE Ratio is a market-oriented discriminating variable describing how much the market participants are willing to pay for one dollar of earnings. Lastly, Cash Conversion or Net Trade Cycle as a discriminating variable is related to the efficiency of a firm in cash management, indicating that in addition to income-generating ability, liquidity is a key factor for discerning the undervalued and overvalued firms. These associations fit well with the work of Phillips, Wu & Yu (2011) who explore the behavioral "push" that expectation can have on firm market values.

2.2. Step 2: Development of the criteria for converting LVS profile of the candidate firms into FAs' recommendations. *2.2.1. Development of the criteria.* We now demonstrate how to use the LVS to develop criteria that lead to the recommendations for profiling our two candidate firms. Here we introduced the use of IQR (inter-quartile range) as a robust fitting metric for profiling the candidate firms. We use this as a reliable test to provide a good fit with the ratings of most of the related Investment Banking reports. This is our suggested operational heuristic. Of course, it may be refined and developed over time. The basic procedure is to locate the candidate firm's actual values on the variables in the Lean Variable Set to determine into which side of the median it falls respecting the two groups: Undervalued Group: "Industry Leading" and Overvalued Group: "Industry Trailing". We note this as the directional IQR for partitioning. In the context of the Fair Value Rating System, directional IQR means that if the variable value of the candidate firm is above the median in the direction of the Undervalued group it would be scored as **positive** or if the variable value of the candidate firm is below the median in the direction of the Overvalued group it would be scored as **negative**. Otherwise, if the actual score of the candidate firm is below the median of the Undervalued firms and above the median of the Overvalued firms it is rated as **neutral**. The following is an overall summary of our suggested scoring taxonomy:

If all variables in the LVS for the candidate firm have variable values that are above the median of the respective IQR, i.e., positive indications, the recommendation will be Strong Buy. If all variables in the LVS for the candidate firm have values that are below the median of the respective IQR, i.e., negative indications, the recommendation will be Strong Sell.

If the majority but not all variables in the Lean Variable Set for the candidate firm have variable values that are above the median of the respective IQR, i.e., positive indications, the recommendation will be Buy. If the majority but not all variables in the LVS for the candidate firm have values that are below the median of the respective IQR, i.e., negative indications, the recommendation will be Sell.

In all other cases, i.e., neutral indications, the recommendation will be Hold.

2.2.2. Convert the LVS profiles of candidate firms into financial analysts' recommendations. We will now illustrate the way that the criteria are carried out to convert the LVS into the final FAs' recommendations for the two candidate firms: Microchip Technology, Inc. (MCHP) and NXP Semiconductor (NXPI).

The actual values of the MCHP for the Fair Value are presented in the following Table 1.

Table 1. Scoring of the candidate firms: MCHP and NXPI on the S&P value rating system

PIVs	Median under valued group	Median overvalued group	MCHP values	FA score indication for MCHP	NXPI values	FA score indication for NXPI
ROA	0.01	-0.05	0.09	Positive	-0.02	Neutral
ROE	0.02	-0.11	0.14	Positive	-0.19	Negative
PE ratio	19.84	-10.63	24.3	Positive	-0.93	Neutral
Total assets turnover	0.55	0.65	0.38	Neutral	0.44	Neutral
Cash conversion or net trade cycle	87.67	72.18	134.7	Positive	41.7	Negative

As shown in Table 1, the actual values of the ROA for MCHP and for NXPI, of our candidate firms were: 0.09 and -0.02, respectively. Since the value of MCHP on ROA is above the median of Undervalued group, i.e., 0.09 > 0.01, the FA score indication for MCHP on ROA is positive. For the same reason the actual value of NXPI on ROA was -0.02 which is **not** on the negative side of the median of -0.05, i.e., -0.05 < -0.02 but **not** above the median of Undervalued group, i.e., 0.01 > -0.02. Therefore, the FA indication for NXPI on ROA is neutral. The same IQR location-logic can be applied to the other LVS variables to convert the other PIV values into the corresponding FA scores for both firms.

After converting the LVS profiles of MCHP and NXPI into the FA scores, we can conclude from Table 1 that because more than a majority, but not all of the score indication of LVS profiling variables for MCHP are in the positive zone, the financial analysts' recommendation based on the aforementioned criteria for MCHP will be: Buy. For NXPI, since more than a majority are Neutral, the FAs' recommendation will be: Hold. As a context check on the TDM our recommendations for these two candidate firms based on our developed criteria are consistent with the real-world investment banking ratings: MCHP was rated positive by SIG (Susquehanna International Group) and NXPI was rated Overweight by Morgan Stanley Research.

3. Scoring System #2: The S&P quality index system with high quality as a positive indication and low quality as a negative indication

3.1. Step 1: Identification of the LVS based on the ratings of the scoring system #2. Based on the S&P Quality Rating index we again formed two groups. The "Industry Leading" group is a High Quality group consisting of firms rated as A or B. The "Industry Trailing" (i.e., Poor Performance) group is a Low Quality group with firms rated as C. We compared the values of variables across these two groups and identified the following 7 discriminating variables out of the 16 independent PIVs (see Appendix C).

3.1.1. Quick Ratio, ROA, ROE, Cash Flow Liquidity, Cash Flow Adequacy, PE Ratio, and Effective Tax Rate. These seven variables constituted our second LVS with respect to the partition of two groups using the S&P quality index scores (i.e., our QUALITY index or historical-relative scoring system #2). These seven variables reveal two relevant qualitative characteristics that distinguish the high quality group from the low quality group of firms. These seven variables pertain to measurement of income quality and can be classified into three categories: (1) the income generating ability of firms (ROA and ROE); (2) the ability of firms in generating cash (Cash Flow Liquidity, Cash Flow Adequacy, and Quick Ratio, and Effective Tax Rate), and (3) the market perception of the income quality (PE ratio).

3.2. Step 2: Development of the criteria for converting LVS profile of the candidate firms into FAs' recommendations. Using the same criteria as explained for scoring system #1, referencing Appendix C, following is the rationale for our recommendations for the two Candidate Firms (MCHP and NXPI) on the second S&P rating for the quality index.

For MCHP, five of the seven of the PIV variables fall above the medians of the High Quality: "Industry Leading" group and so would be recommended as a Buy on the quality index. NXPI has four of the seven PIV variable values which fall below the medians of the Low Quality: "Industry Trailing" group so would be recommended a Sell. Again, our recommendations for these two candidate firms with respect to the quality index system are consistent with the investment banking ratings: MCHP was rated Positive by SIG and NXPI was rated Overweight by Morgan Stanley Research.

In summary, the two indications based on the two independent criteria developed from the two scoring systems are: MCHP: (S&P: Value (Buy), S&P: Quality: (Buy)) and NXPI: (S&P: Value (Hold), S&P: Quality: (Sell)); these fit well in the context of the ratings provided by SIG and by Morgan Stanley Research as indicated above. How the FA weights these two indications is beyond the scope of the paper. However, for example, if the Value and Quality indices were equally important to the FA, conservatively the FA may recommend MCHP: Buy and NXPI: Sell.

Conclusion

We have demonstrated the application of the five-stage TDM for FA to extract parsimonious information from financial statement analysis for making recommendations. The independent recommendations based on each of the two scoring systems at the last stage of the TDM are consistent with the Investment Banking ratings as we intentionally chose two candidate firms with different performance profiles as a reasonability check. However, in practice, we have often found that the recommendations differ, sometime dramatically, depending upon the different evaluation partitions used. When we find, as we did for the Fair Value and the Quality ratings, that the two candidate firms: MCHP and NXPI, remain in the same FA grouping: Buy and Sell respectively this is convincing information on the benchmark rating of the firms. We offer this as a "robustness check" on the FSA classification suggesting that whether an investor is looking forward or characterizing the past performance the firms remain in the same grouping.

A note of extended use of the TDM: when the TDM is used for the profiling then it is the case that, in effect, the FA recommendations are forecasts. In this case, the financial analysts should validate the forecasts as a means of closing the feedback loop. We are mentioning this because for almost all investment banking forecasts there is rarely feedback on the accuracy of the recommendations. Therefore, we suggest that the FAs' recommendations be tracked and evaluated. This "post-auditing" of the recommendations may be useful in calibrating the time frame for which the recommendations are useful as well as the nature of the comprehensive variable set that is used to start the process. It is, of course, the case that the more variables that FAs use at the beginning of the process, the more effective the TDM can be. In fact, this is one of the principal benefits of the TDM; no matter how many variables the financial analysts begin with the final set will be a dramatically reduced subset. For example, we start the process with 31 variables in the CVS. In either Scoring System, we have observed an 80% average reduction from the CVS to the LVS using the TDM.

As a final note, one of the important aspects of this TDM is the ease of understanding the model so that it can be used with confidence by the FA in the Investment Banking (IB) firm. To develop information that addresses the issue of "ease-of-use" we used this TDM in a Financial Statement Analysis course in the MBA Program at the American University of Armenia, 2010. The language of instruction was English and the Instructor is a native speaker. We presented the information for the TDM over the course and tested the understanding of the model using the results of a case study that was done by self-selected groups of students. The groups ranged from two to four students. They were given the datasets and had two days to complete the IB-profiling report for two organizations. The two organizations were intentionally selected to be at diverse ends of the performance profile, i.e., an "Industry Leading" and an "Industry Trailing" performer. One of the authors, who presented the FSA course, was available as a "technical" consultant so students could pose any questions as to how the TDM should be applied as it related to the JMP software or statistical issues that were not clear. For the nine groups of 26 students in total there were only two questions; each of which dealt with how to use the JMP/SAS software to eliminate outliers and was resolved after a few minutes of discussion. All of the groups completed the exercise; there was a "solution" to the exercise that was prepared so as to "grade" their IB-profiles. All of the groups correctly identified the "Industry Leading" and "Industry Trailing" performers. All of the groups made the same FA decisions: Buy and Sell except one group that scored the two firm candidates as Strong Buy and Sell. We offer this as case-specific information that the TDM seemed to work well for this group of reasonable surrogates for junior FA. All of the educational material is available from the corresponding author by request. Such information can be a valuable in training for either academic courses or IB-firm workshops.

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Appendix A

Table 1A. Variables selected from Fraser & Ormiston (2009)

Current Ratio	Current assets/Current liabilities
Quick Ratio	(Current assets-Inventory)/Current liabilities
Cash Flow Liquidity	(Cash + Marketable securities + Cash flow from operating activities)/Current liabilities
Average Collection Period	Net accounts receivable/Average daily sales
Days Inventory Held	Inventory/Average daily cost of sales
Days Payable Outstanding	Average payable/Average daily cost of sales
Cash Conversion or Net Trade Cycle	Average collection period + Days inventory held – Days payable outstanding
Accounts Receivable Turnover	Net sales/Net accounts receivable
Inventory Turnover	Cost of goods sold/Inventories
Payable Turnover	
Fixed Assets Turnover	Net sales/Net PPE
Total Assets Turnover	Net sales/Total assets
Debt Ratio	Total liabilities/Total assets
Debt to Equity Ratio	Total liabilities/Total stockholders' equity
Financial Leverage Index	Return on equity/Adjusted return on assets
Return on Assets	Net earnings/Total assets
Return on Equity	Net earnings/Stockholders' equity
Cash Flow Margin	Cash flows from operating activities/Net sales
Gross Profit Margin	Gross profit/Net sales
Operating Profit Margin	Operating profit/Net sales
Effective Tax Rate	Income taxes/Earnings before income taxes
Net Profit Margin	Net profit/Net sales
Cash Flow Adequacy	Cash flows from operating activities/(Capital expenditure + Debt repayments + Dividends paid)
EPS Increase	One-year change in EPS (%)
PE	Market price of common stock/Earnings per share
Cash Return on Assets	Cash flow from operating activities/Total assets
Dividends Payout	Dividends per share/Earnings per share
Dividends Yield	Dividends per share/Market price of common stock
Long-term Debt to Total Capitalization	Long-term debt/(Long term debt + stockholders' equity)
Cash Interest Coverage	(Cash flow from operating activities +interest paid + Taxes paid)/interest paid
Times Interest Cearned	Operating Profit/Interest expense

Appendix B

Table 2B. Factor rotated matrix from which we selected PIVs

	F1	F2	F3	F4	F5	F6	F7	F8
Current Ratio	0.075935	0.885763	0.085581	0.158296	0.228255	-0.16161	0.013775	0.015867
Quick Ratio	0.078582	**0.896103**	0.024014	0.175855	0.174215	-0.15882	-0.00081	0.032367
Cash Flow Liquidity	0.294465	-0.13189	-0.06615	0.12262	-0.13285	-0.08451	-0.59275	0.132125
Average Collection Period	-0.1788	-0.16941	0.05915	-0.90967	-0.12692	0.0097	-0.00361	-0.01419
Days inventory held	-0.0773	0.070761	0.94668	-0.03864	-0.09214	-0.02996	0.015116	-0.00372
Days Payable Outstanding	-0.16345	-0.14964	0.146775	-0.14013	-0.885	-0.03199	0.001471	0.011483
Cash Conversion or net trade cycle	-0.00147	0.114394	0.691729	-0.28818	0.609074	0.005653	0.009906	-0.01849
A/R Turnover	0.157375	0.172259	-0.08503	**0.891985**	0.118948	0.02082	0.117131	-0.01901
Inventory Turnover	0.024276	-0.1154	**-0.90317**	-0.03174	0.029945	-0.00996	0.016955	-0.00293
Payable Turnover	0.194631	0.14221	0.076016	0.142601	**0.821866**	-0.07885	0.02402	0.036383
Fixed Assets Turnover	0.132472	0.005199	0.045307	0.190173	-0.17855	-0.01944	**0.799082**	0.239351
Total Assets Turnover	0.067172	-0.45686	-0.21339	0.141868	0.160963	-0.06444	0.59537	-0.17088
Debt to Asset Ratio	-0.08226	-0.63767	-0.15307	-0.11212	0.019035	0.272761	-0.00198	-0.1023
Debt to Equity Ratio	-0.10808	-0.23195	-0.0092	-0.00309	-0.01783	**0.949649**	0.011555	-0.00502
ROA	**0.90061**	0.119336	-0.02387	0.137077	0.084117	0.008982	-0.02821	-0.05545
ROE	0.60866	0.153126	-0.05749	0.081364	-0.03107	-0.35138	-0.0859	-0.13151
Financial Leverage Index	-0.11221	-0.23347	-0.01208	-0.00556	-0.0164	0.948295	0.002677	-0.00335
Cash Flow Adequacy	0.629012	0.057028	-0.01382	0.045794	-0.05186	-0.07837	0.180349	0.451318

Table 2B (cont.). Factor rotated matrix from which we selected PIVs

	F1	F2	F3	F4	F5	F6	F7	F8
Gross Profit Margin	0.313061	0.249296	0.265484	0.450319	-0.37705	-0.17571	0.024544	0.196461
Operating Profit Margin	0.918469	-0.03709	0.021727	0.08081	0.138419	-0.07194	0.011045	0.066178
Net Profit Margin	0.929901	0.053369	-0.0062	0.061018	0.130748	0.008256	0.071511	-0.04762
Cash Flow Margin	0.782784	-0.06983	0.079102	0.149678	0.082725	-0.13508	-0.30328	0.26955
Cash Return on Assets	0.781723	-0.14445	-0.0809	0.237466	0.149304	-0.17579	-0.16852	0.183871
EPS increase (%)	0.759808	0.28173	-0.09227	-0.05059	-0.02312	0.097089	0.123819	-0.12645
PE Ratio	0.196017	0.139475	0.007303	-0.10719	-0.01142	0.070143	-0.09369	0.602002
Effective Tax rate	0.364751	0.025131	0.022659	-0.26847	-0.04774	0.08862	-0.14397	-0.56687

Appendix C

Table 3C. Comparison between two groups to identify discriminating variables from the 16 independent PIVs: One Way Median Test

	Fair Value Rating Undervalued group: 4 or 5 Overvalued group: 1 or 2				
PIVs	Median Undervalued group	Median Overvalued group	Chi-square	P-value	Discriminating PIV? (Y/N)
ROA	0.01	-0.05	3.96	0.047	Yes
ROE	0.02	-0.11	7.05	0.008	Yes
PE Ratio	19.84	-10.63	7.05	0.008	Yes
Total Assets Turnover	0.55	0.65	3.96	0.0465	Yes
Cash Conversion or Net Trade Cycle	87.67	72.18	3.96	0.047	Yes
	Quality Rating Index High Quality: A, B Low Quality: C				
PIVs	Median high quality	Median low quality	Chi-square	P-value	Discriminating PIV? (Y/N)
Quick Ratio	3.84	2.46	5.17	0.023	Yes
ROA	0.02	-0.09	21.75	0.000	Yes
ROE	0.03	-0.12	13.74	0.000	Yes
Cash Flow Liquidity	443.01	149.22	5.17	0.023	Yes
Cash Flow Adequacy	2.83	0.91	7.57	0.006	Yes
PE Ratio	30.15	-4.32	10.43	0.001	Yes
Effective Tax Rate	0.20	0	17.52	0.000	Yes