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Title:	A Model for Rating Wall Street Analysts Using DEA
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Abstract: In this paper, the drawbacks of the current model used to evaluate the stock picking skills of Wall Street analysts is discussed and an alternative model developed using "Data Envelopment Analysis" is explained.

A Model for Rating Wall Street Analysts Using DEA

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Also, since each investment opportunity is linked to a risk, we use *beta* as its measure. *Beta* is a standardized measure of risk of a security. If the change in a security value correlates perfectly and moves in the same direction with the same percent change as the market, the *beta* for the security is said to be 1.0. Conversely, if there is no change in the price of a security for any change in the value of a market portfolio, the *beta* for that stock is considered to be 0.

Next we define what we mean by market. Market or market portfolio is a portfolio composed of all securities in proportion to their value. One such indicator of market portfolio is the S&P 500 index. If this index rises (or falls) there is a tendency for individual stocks to rise (or fall), although the sensitivity of each stock or its *beta* will be different depending upon stock's fundamental characteristics.

Thus in the context of evaluating the analyst's performance, each analyst's portfolio comprises of a measure of its return(its portfolio value) and a measure of its risk(as defined by its *beta).* The 90 day Treasury Bill is considered to be the risk free investment.

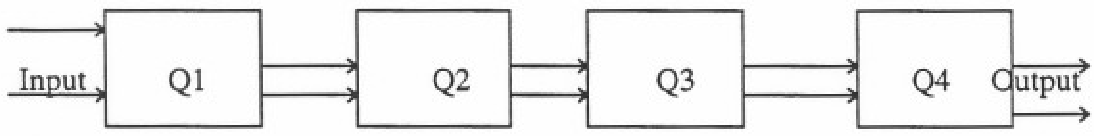
5. An alternate model using DEA

With this available information, we can develop a DEA model for evaluating an analyst's efficiency. Since the output of each analyst's work is his/her portfolio, the portfolio value becomes one measure of the efficiency. *Beta* of the portfolio becomes the other measure of the efficiency since risk and return go together. These 2 measures become the output of our DEA model.

Now we consider the inputs to this model. As all the analysts in this survey work for big wall street firms, we presume that all the analysts have the necessary infrastructure and information support to conduct their research. Therefore, it is reasonable to assume that no analyst has any special advantage over other analysts.

Since we are interested in the performance of an over 1 year, each analyst's performance is divided over 4 quarters of the financial year. The portfolio value and the portfolio beta from the first quarter become the inputs for the second quarter. Thus we have two inputs and two outputs in our model. These inputs and outputs are referred to as VALIN, BETAIN, VALOUT and BETAOUT in the AMPL representation of this model.

The data flow for the 4 quarters are as shown below:



5.1 Justification for using DEA to perform this evaluation

DEA can be used for this application because:

-it helps identify the best practices and in this application we are attempting to identify the wall street analyst(s) with the best performance

-this model has multiple inputs and outputs each with different units of measurements and DEA is capable of handling such inputs and outputs.

-the DEA analysis can produce a single aggregate measure of efficiency for each analyst. DEA can also provide the ideal performance target for an inefficient analyst.

-efficiency results which have impact on dollars and cents are easy to understand

5.2 Assumptions for the DEA model

If two portfolios provide the same rate of return then a portfolio with a lower *beta* is more desirable to the portfolio with a higher *beta*. Therefore our aim is to drive the portfolio *beta* value down and make the portfolio less riskier. Since the DEA uses a production function equation, if the input values go up it is reasonable to expect the output to go up. Furthermore, a portfolio can have a *beta* of 0.0 if it is invested totally in T-bills. Thus a *beta* with 0.0 value will cause problems in DEA formulations. Therefore we need to apply some correction to the *beta* value of the portfolio as follows.

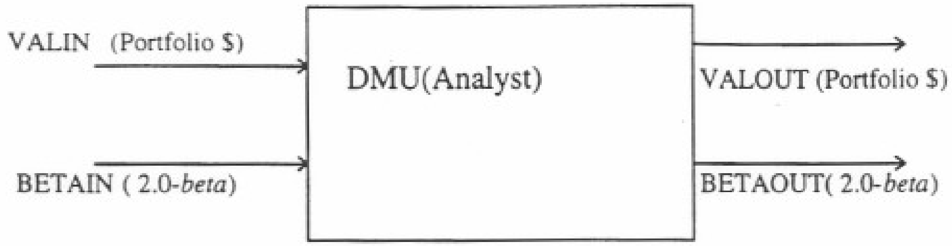
In theory there is no limit on *beta* values but in reality most of them fall in the range of 0.5 to 1.5. Also a *beta* with negative values is theoretical possibility but not a single stock with a negative *beta* has been spotted[Appendix 2] . Thus we can make the following 2 assumptions regarding *beta* values that:

-they have an upper limit of 2.0

-they are not negative.

With these two assumptions, we can subtract the portfolio *beta* values from 2.0 to get BETAIN and BETAOUT for input and output respectively.

In our attempt to use DEA to evaluate analyst efficiencies, we are trying to identify the best performing analyst with regard to portfolio return and portfolio risk. The model is as shown below:



With this correction in *beta* values, the model now correctly represents a desired behavior of analyst. This means that the best performing portfolio can exist with either high VALOUT (high portfolio value) or high BETAOUT (low *beta* value).

5.3 Choosing the appropriate DEA model

The above model describes a Decision Making Unit(DMU) for our analysis. A DMU can be constructed by calculating the portfolio return and risk at the end of each quarter for each analyst.

We have to choose the appropriate DEA model by asking the following questions:

- Is it reasonable to assume a CRS(Constant Return to Scale) in this DEA model?

DEA evaluates the performance of each DMU by constructing a virtual DMU. This virtual DMU is a combination of one or more best performing DMUs and represents the target for an inefficient DMU.

If we assume CRS then it means that a virtual DMU can be freely formed from the DMU's

operating on a much larger or a much smaller scale. In our case, the portfolio value ($1000) is hypothetical and hence is not a factor in determining the scale of a DMU. The other candidate to determine the scale of operation is the size of the firm which an analyst belongs to. Hence we ask ourselves "does an analyst working for a big firm have an advantage (scale of operations) over an analyst working for a smaller firm and is it fair to compare these two analysts?". It can be seen that an analyst from a big firm does not have a significant advantage over an analyst from a small firm and hence it is fair to compare them. Therefore we are justified in assuming CRS and a virtual (or best performer) DMU can be freely constructed from the combination of other DMU's.

- Is the problem oriented towards output maximization, input minimization or a combination of both?

Our objective here is to identify the best performers with regard to portfolio return and portfolio risk. Therefore we should maximize VALOUT and BETAOUT.

We should choose a DEA model which performs output maximization for a given set of inputs. In this case we will be using an output oriented envelopment (CCR) model. The equation of the model is as follows:

$$\max \phi \text{ s.t}$$

$$X\lambda <= Xo$$

$$Y\lambda >= \phi.Yo$$

$$\lambda >= 0$$

where X vector represents inputs, Y vector represents outputs, ϕ scalar represents the efficiency, λ vector represents the virtual multiplier. Xo and Yo are the input and output of a specific DMU under consideration. This model can also be represented using a linear programming formulation and its AMPL representation is shown in Appendix 6.

5.4 Assumptions for the DEA model

1. We will evaluate all the analysts who follow a specific industry (say Airlines) for their stock picking skills in this industry.
2. Each analyst starts with a fixed amount in the portfolio ($1000) at the beginning of the year and can make stock purchases only from this amount.
3. Each analyst can recommend a "buy" and "sell" as many times as he/she wants but will incur a fixed transaction cost for each buy and sell operation (including T-bills).
4. A portfolio at any time, cannot contain more than a fixed number of stocks.
5. If the analyst has no active recommendation at any time, the money is invested in T-bills(which have a β of 0)
6. We will measure the analyst's performance at the end of each quarter-31 March, 30 June, 30 September and 31 December in 1997.

5.5 DMU and data collection for the model.

As per our definition, the performance of an analyst is determined by the performance of the hypothetical portfolio ascribed to the analyst. Thus each analyst's portfolio value taken at the end of each quarter becomes a DMU of the model. This model evaluates 5 analysts and they are named DMU -A, B, C, D & E. For this project, I collected the following data:

Portfolio value is the output which is measured in $. This is referred to as VALIN and VALOUT in the AMPL model. This value is computed at the end of each quarter for each DMU.

Portfolio *beta* is the *beta* of the portfolio. This is calculated by weighted average of all the investments in the analyst's portfolio. As described in the previous sections the *beta* value is subtracted from 2.0 to obtain BETAIN and BETAOUT in the AMPL model. Both VALOUT and BETAOUT of the any quarter are the input VALIN and BETAIN to the next quarter. First quarter VALIN and BETAIN are $1000 and 2.0 respectively. There are 4 sets of data representing each quarter in 1997.

6. AMPL model

This model was solved using the 2 phase approach which involved the use of slack variables in inputs and outputs. The programming was done in AMPL and the copy is enclosed in the appendix 6. This model computed the efficiency and the slacks in each DMU's input and output for the 4 quarters.

6.1 Raw data

The data used for this computation is shown in Appendix 3 . It shows VALIN, BETAIN, VALOUT and BETAOUT for all the 5 analysts for 4 quarters of FY 1997. All these analysts were following the airlines industry and had their portfolio comprise of the stocks from this industry. The *beta* values for each of the stocks were obtained from yahoo website and are shown in Appendix -5. However, since the actual composition of the portfolio was not available I have taken hypothetical values for the portfolio values(and hence their *beta*).

7. Interpreting the DEA Results

The results of the model are shown in the Appendix 4 . The results show "phi" (the output oriented analyst efficiency), the input slack "s_x", output slack "s_y" and the virtuals(lambda multipliers) for each DMU.

7.1 Efficiency

It is the output oriented efficiency of a DMU which tells us how efficient the DMU has been in generating these outputs. A score of 1.0 is the best score of efficiency and indicates that the DMU is a "best performer". For inefficient DMU's with efficiency score of >1.0 indicates the amount by which the DMU can improve its output. This is a measure of its efficiency based on its peer performers. Many observations can be made from these results. In the first quarter all the analysts start off with a fixed sum of cash (a least risky investment) and buy shares with it. As the year proceeds, they make many buy and sell decisions which affect their portfolio values. DMU's D and E show wide fluctuations in their efficiency values whereas DMU's A and C show some changes across the 4 quarters. DMU B has its efficiency scores unchanged.

An interesting situation arises if we eliminate the intermediate financial quarters by collapsing the model and consider only one input (inputs to Q1) and one output (output from Q4) in the model. The results result from this model is shown in appendix 4. It can be seen that only DMU C is efficient now and all other DMU's are inefficient by a big amount. This result is different from the Q4 result in which DMU A,B,C & E were found efficient. In fact, as per the original WSJ survey, DMU C would have been judged the most efficient followed by E, B, A & D. The results from the collapsed model show that

C is the most efficient followed by DMU B, E, D & A. This would be hard to accept because DMU E produces a better return compared to B and DMU A produces a better return than D. But we can say that DMU E took more than "necessary" risk as compared to his/her peers to obtain its portfolio value and hence is rated lower than DMU B.

7.2 Lambda values

These are the virtual multiplier values. For each DMU, it tells how its virtual performer is being built. The virtual performer is the target for an inefficient DMU. For an efficient DMU the virtual performer is itself. In Q1, DMU D has a virtual performer built from 0.022 portions of DMU B and 0.978 portions of DMU E. Efficient DMU's are their own targets and inefficient DMU's have a combination of other DMU's as their target.
It can also be seen that the sum of virtuals for some DMU's (for example DMU D in Q2) add up to 1. This is not surprising because we assumed a CRS model.

7.3 Slack variables

Slack variables indicate the amount of slack that is hidden in the DMU's performance. For a DMU to be truly efficient, not only its efficiency score should be 1.0 but also its slacks should be 0.0. In Q3, DMU E shows a slack of 0.182 in BETAOUT. Since its efficiency in Q3 is 1.23, the desired BETAOUT from DMU E in Q3 should be 0.55*1.23 + 0.182 = 0.858.

These results also provide us other insights into computation of a DMU's efficiency. If the efficiency is calculated based only upon the return in portfolio value then some

DMU's may not be 100% efficient but these DMU's might become efficient if DEA is used instead. Similarly, some DMU's that are efficient based on portfolio value calculations might become inefficient if measured with DEA. For example, in Q3 results, DMU B is considered efficient ("phi" = 1.0) whereas it would have ranked lowest if it were measured using portfolio value only. Similarly DMU D is inefficient with "phi" value of 1.53 but if we were to measure its efficiency based only on portfolio return, it would rank 2nd in the group. Thus the inclusion of *beta* values in the DEA provides another dimension to measure an analyst's efficiency.

8. Other DEA models

It is possible to model this problem using a different DEA construct to provide answers to questions an investor may ask. For example, if an investor were to say that the returns on portfolio is more important than the risk by a factor of 2:1 then we could develop a ranking of the analysts based on this investment preference. We would then construct a DEA multiplier model with weight restrictions to get a different set of analyst rankings.

9. Summary

In this report we have seen that DEA can be used to evaluate an stock analyst's efficiency based on the factors that are important in portfolio management. These factors have different units of measure and DEA provides us a way by which can take these inputs and get single efficiency score. This model is based on many assumptions and it is possible to build a more rigorous model. But this model has demonstrated that it is possible to consider both risk and return in evaluating an analyst's efficiency. By evaluating the analysts over 4 quarters, this model has shown that it is possible to identify the investment traits of various analysts and select a trait that is suitable for each investor.

10. Acknowledgment

I am thankful to Dr. Tim Anderson for guiding me in this project.

11. Appendix

1. Wall Street Journal clippings explaining the present survey method.
2. Excerpts from Financial management [Reference 3] regarding assumptions on *beta* values.
3. Excel work sheet containing the Raw Data used for analysis.
4. Excel work sheet containing the computed values from DEA model.
5. Profile of the companies from the airlines industry that were part of the portfolio in this analysis.
6. AMPL model- .mod , and .run files.

12. References

1. *Data Envelopment analysis: Theory, Methodology and Applications* edited by Charnes, Cooper, Lewin and Seiford.
2. *Productivity Measurement Using DEA-EMGT 537 course notes* by T.R.Anderson.
3. *Financial Management: Theory and Practice* by Brigham and Gapenski.
4. *Modern Portfolio Theory: The principles of Investment Management* by Rudd and Clasing Jr.
5. *Wall Street Journal: All star survey supplement* on 30 June 1998.