Time to Fulfillment of Stock Recommendations Based on Technical Analysis: A Survival Analysis Approach

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Abstract

Stock recommendations based on technical analysis have been evaluated by researchers in terms of the abnormal excess returns generated compared to some benchmark return. Here, instead of looking at the magnitude of excess returns, we study the liquidity of trading strategies based on analyst recommendations as an indicator of their efficacy. We use an event study methodology for 403 technical calls published over a period of four years from 2011 to 2015 on an online finance portal. Parametric survival models were built to understand the factors that might affect the time taken for a stock to reach the targeted sell/buy price. Lower targeted returns, a bullish market trend, and greater volumes of trading in the pre-recommendation period lead to smaller times to fulfillment for technical calls. However, consistent with other studies, we find that analysts using technical analysis have not been able to provide recommendations that consistently yield high returns in a short period of time.

Key words: Analyst Recommendations, Technical Analysis, Survival Analysis, Indian stock market, Liquidity

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Introduction

Financial experts and stock market analysts provide "buy" and "sell" recommendations for individual stocks that are followed by a large population of individual and institutional investors. In India, an emerging market, as the number of individual investors has increased rapidly over the last two decades, the industry of providing stock trading tips and advice has also flourished. Experts offer their advice through newspapers (Financial Express/Economic Times), TV channels (NDTV Profit / Zee Business / ET Now etc.) as well as finance portals such as "yahoo-finance" and ""money-control.com" etc.

The ubiquitous reach of the web and the implications for information dissemination in financial markets have been discussed by Orazov (2008). Small investors rely on web based stock recommendations more than sophisticated large investors (Mikhail et. al, 2007). Web based analyst recommendations may have a cascading effect causing large swings in a scrip one way or the other (Hirshleifer and Hong, 2003), and might affect the financial well-being of a large number of small investors. Some researchers have started looking at the effect of social media on investor mood which might in turn affect stock markets.

Motivation of Study

Given the possible reach and impact of online analyst recommendation, it is important to evaluate the quality of the advice available through financial portals on the web such as "yahoo-finance" or "Indiainfoline.cm". This issue is the primary motivation for this study. Stock market traders are often concerned not only with the expected returns of their trading strategies but also the liquidity of their positions. An individual whose money is tied up in a given strategy would usually be interested in the amount of time that she has to wait before realising the gains from trading. One has to take into account the opportunity cost of having money tied up in certain stocks as the investor waits for the target price to be reached. As far as we could determine, no studies have looked at the duration or *time* aspect of trading strategies that depend on analyst recommendations.

There have been numerous studies that have looked at the profitability of analyst recommendations. However, in all of these studies, the metric used for measuring analyst efficacy was the excess returns generated by following these recommendations compared to the strategy of buy and hold or the returns from a benchmark index. Brown (1993) had suggested that researching the 'same old' issues using the 'same old' methodologies would not remain informative, and one might eventually try to identify interesting new questions and design interesting and meaningful empirical tests. Despite such early concerns, the considerable volume of literature[3] in this field has continued to focus on excess returns. In this study, we have looked at this issue from a different perspective viz. the liquidity of the recommended positions and have used different empirical methods viz. survival analysis techniques.

[3] A search on Google scholar with the Keywords: analyst recommendations" and "excess returns" yields almost 1000 results.

In this paper, we analyse the liquidity aspect of analyst advice by building survival analysis models using archival data of recommendations posted on a finance portal. The recommendations we have included in this study were made on the basis of technical analysis as opposed to fundamental analysis. Technical analysis typically uses recent price movements and heuristic rules / time-series models to arrive at the predictions of price movements while fundamental analysis entails research conducted into the financial condition of each individual company and an understanding of its competitors and the economy. After detailed analysis, fundamental analysts recommend undervalued stocks for "buy" and overvalued stocks for "sell" purposes. In technical analysis, all relevant information is assumed to be incorporated in the stock price and the stock price is assumed to adjust quickly in response to any news. In fundamental analysis the assumption is that stock prices are sticky and markets are not efficient.

The time taken by the stock to reach the recommended target price was first analysed using non-parametric methods, namely Kaplan Meier Survival plots. Parametric accelerated failure time models were then used to understand the influence of several factors that might affect the time to fulfilment of these strategies. The rest of the paper is organized as follows: in the next section we provide a review of the literature that has looked at efficacy of analyst recommendations, then we give an overview of the methodology including the data and the models to be used for analyzing the liquidity aspect, finally we discuss the results and conclude with our main findings.

Literature Review

There have been numerous empirical studies in the last thirty years that have looked at the efficacy and profitability of analyst recommendations[4]. Many of these studies have looked at the efficacy of analyst recommendations in the US, but there are some studies that have also looked at other countries such as Italy, Russia, Australia and India. To give the reader an overall idea of the literature, we mention some papers that provide a comprehensive review of the literature in this field. We also mention some of the more recent studies (subsequent to the latest review paper) to give a more updated understanding of the state of the art in this field.

Review papers

Schipper (1991) and Brown (1993) were early papers that reviewed the literature in analyst recommendations. Schipper (1991) emphasized the need to understand the decision processes and biases in such decision making along with the outputs of their analysis. Brown (1993) specifically commented on the statistical properties of the earnings forecasts and also the association between earnings forecast and capital market research. Schuster (2003) reviewed 33 studies published between 1978 and 2001 and found that reports published in most financial media lacked any real new information. The study concluded that there is no evidence that stock

[4] It may be noted that many researchers have looked at the efficacy of technical analysis rules by implementing and evaluating forecasts generated by these rules. However, in this study, we are concerned not with the efficacy of the rules but of the analysts using those rules and providing recommendations for the retail investor.

recommendations offer any systematic opportunity to outperform the market and investors who follow such advice will lose in the long run.

Ramnath, Rock and Shane (2008) provide a comprehensive review of the literature around analyst recommendations. They reviewed a total of 233 studies in the period 1991 to 2005, and classified the literature into seven categories based on the following concepts: (i) analysts' decision processes, (ii) the nature of analyst expertise and the distributions of earnings forecasts, (iii) the information content of analyst research, (iv) analyst and market efficiency, (v) analysts' incentives and behavioural biases, (vi) the effects of the institutional and regulatory environment (including cross-country comparisons) and (vii) research design issues. The comprehensive taxonomy was useful in giving the reader an overview of the extant literature.

In an interesting review of 95 studies spanning four decades from 1968 to 2008 Bradshaw (2011) states that despite a deluge of academic activity in this field in the last four decades, the state of knowledge has not advanced correspondingly. Bradshaw summarized the findings with the following observations: (i) analysts' forecasts are optimistic, (ii) they are superior to time-series model forecasts, (iii) analyst forecasts are inefficient, (iv) academic research ignores analysts' multi-tasking, (v) analysts face conflicts of interest in the form of investment banking fees and currying favour with management among others, (vi) limited evidence exists regarding how analysts arrive at their recommendations and also about what the analysts do with their own forecasts, (vii) the empirical methodology employed in evaluating the quality of the analyst recommendations is limited in that it focuses on abnormal excess returns[5], and (vii) analyst's contributions to the financial knowhow is not completely captured by just quantitative analysis of their recommendations. However he concludes his article by noting that a positive by-product of research into analyst activity is that it may shed light on several aspects of capital market research such as asset pricing anomalies etc.

Most recently, Kothari et al. (2016) reviewed the literature on sell-side analysts' forecasts and their implications for asset pricing by incorporating the idea of supply and demand forces shaping analysts' forecasting decisions. Like Schipper and Bradshaw, Kothari et al. note that the specific mechanisms through which analysts' forecasts influence asset prices have not been clearly understood despite the presence of substantial literature in this area.

Research after 2008

Since there have been several comprehensive reviews of literature for papers up to 2008 and since most of these studies were based in the US, in the rest of this literature review we discuss studies that were published post 2008. The following literature review is not comprehensive, but is meant to be representative. We have tried to include a study from each year post 2008 and we have also tried to include studies from different parts of the world other than US, viz. Australia, Thailand, Greece, Germany, Sweden and 11 emerging markets (see footnote 4 below).

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[5] It may be noted that in this study we are not looking at excess returns and thus we are addressing one of the research gaps in the literature as pointed out by Bradshaw.

Moshirian, Ng and Wu (2009) analysed 2432 firms comprising of 27,982 buy recommendations and 1677 firms with 19783 sell recommendations, in 11 emerging markets[6] and based on computation of buy-and-hold abnormal returns (BHAR) found that, stock markets react positively to analyst recommendations and analysts recommend stocks with large Market-to-Book ratios. They also conclude that stock analysts in emerging markets favour high growth stocks with attractive characteristics.

Lonkani et al. (2010) studied 11,461 recommendations from the Thai Stock Exchange in the period 1993-2002 and found that there were some abnormal excess returns associated with strong buy recommendations. They also found some evidence of leakage of information since abnormal returns were found pre-announcement date also. Glezakos and Merika (2011) analyzed 727 recommendations over the period 1/8/2004-31/7/2005 with data from the Athens Stock exchange and concluded that these recommendations do not result in any significant excess returns.

Andersson and Eriksson (2013) looked at 450 recommendations between the period of 2011 and 2012 from Placera which is one of Sweden's largest business websites. They do not find evidence of any abnormal excess returns based on analyst recommendations. They did not find any differences in large, mid and small cap stocks. However, they found that "sell" recommendations outperformed "buy" recommendations.

Smith et al. (2013) studied the efficacy of analysts that use technical analysis for their recommendations. In the sample of about 10,000 portfolios that they studied, one third of the actively managed equity funds used technical analysis. They found that while the benchmark adjusted returns of funds using technical analysis was slightly higher; the volatility of the returns, skewness and kurtosis was also higher.

Medovikov (2014) analysed I/B/E/S monthly recommendations for the period January–December 2011 with excess security returns during six months following recommendation issue. Using a mixed Gaussian–symmetrised Joe–Clayton copula model he found that the "buy" recommendations may outperform the market substantially, though the "sell" recommendations may not underperform relative to the market. They also found that the predictive ability is conditional on recommendation changes.

Analyst Recommendation Literature in India

The literature on the efficacy of analyst recommendations in India is not large.

Chakrabarti (2004) looked at 2000 recommendations made by analysts from 26 brokerage firms for 303 companies in the period January 1998 to July 2003. He calculated excess returns on the same day, after three days, one week, one month and three months, and concluded that brokerage analysts in India are indeed able to predict winners and losers, at least over a four month forecast window. Analyst's predictions actually have greater investment value on the "strong buy" side than on the "strong sell" category.

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[6] Argentina, Brazil, China, Chile, Hungary, India, Indonesia, Israel, Korea, Mexico and South Africa.

Gupta and Singla (2008) used recommendations made in a popular financial newspaper, Economic Times, in the period Jan 2003 to December 2004 and using the method followed by Chakrabarti (2004), calculated excess returns on the same day, after three days, one week, one month and three months. However, they did not find evidence of abnormal excess returns generated by following news in financial media such as Economic Times.

Choudhary and Bajaj (2011) used the Sharpe Performance Measure to capture the impact of analysts' recommendations over 222 buying recommendations in the time period from July 4, 2005 to December 31, 2007. They could not find evidence of abnormal return associated with the publication event of equity analysts' recommendations in Indian capital market.

Sayed and Chaklader (2014) investigated the contribution (if any) of sell side analysts towards profitable investment decisions for investors in India. Using a sample of 1,000 target prices issued with buy ratings between 2007 and 2011, to investigate if investors have benefitted from these target price forecasts, they found that investors, to some extent, can rely on equity research in India for profit-making investment decisions in stocks. In this study the authors calculated the average number of correct predictions made by individual brokerage houses in a given year. In this study there was some information loss due to averaging the results across several recommendations instead of analyzing each recommendation separately.

Overall, we find that out of the four studies related to analyst performance in the Indian context, only one reported unequivocal success of the analyst recommended strategies and none did so after 2004. A few common threads emerge in our review of the literature:

i) Few studies report that analyst recommendations have significant predictive ability which supports the idea of weak form efficient markets
ii) "Sell" recommendations are less frequent than "buy" recommendations indicating that most analysts prefer to be more optimistic; however since sell recommendations are issued with greater caution, their predictive ability is higher.
iii) Analysts tend to recommend well known stocks that are highly traded (glamour stocks).

Methodology

The recommendations we collected are not classified according to the categories above; instead they specify a target price. In this our data is similar to the data from the Athens Stock Exchange analyzed by Glezakos and Merika (2003). In that paper, the authors had categorized the recommendations into the discrete categories mentioned above; and had as such lost some resolution in their analysis. In our approach, the event of the stock price reaching the targeted value within the given time frame[7] is examined from a survival analysis viewpoint and we model the effect of different independent variables that might affect the survival times.

We try to address the following two research questions in this study.

[7] Technical calls that are based on recent price movements are often thought to be useful for a shorter time frame - sometimes as short as a few days or a couple of weeks. Keeping this in mind, we look at a time frame of a month for technical calls.

a) How effective are recommendations made by financial experts? What percentage of buy (sell) recommendations reaches the targeted selling (buying) price within given time frame?
b) How *long* does it take for the recommended stock to reach the target selling price? What are the factors that affect the time taken to reach the target selling price?

Data

The technical analysis calls analyzed for this study came from a sample of 270 buy and 133 sell recommendations for individual stocks, made during March 2011 to March 2015 on the portal indianotes.com[8]. Analyst recommendations, for the "buy" case for example, state a target selling price (abbreviated here as TSP) which is higher than the current price, a stop loss price (lower than the current price), and a time frame for the predicted movement. A typical buy recommendation is given in Appendix I.

We also collected daily price and volume data for each recommended stock for 90 trading days prior to the recommendation and 30 trading days after the recommendation. This data was used to compute the variables described below, which we thought might affect the probability of the targeted price being reached.

Dependent Variable

The time taken for the stock price to reach the Targeted Selling (Buying) Price was the dependent variable. This was censored data since a large percentage of the orders (59% on the buy side) did not reach the TSP within an interval of 30 trading days after the recommendation. If the price was reached, then the event was said to have occurred. If the price was not reached within this window, then the data point is right censored data.

Independent variables

After considering the economics of trading and a review of the analyst recommendation literature, the following independent variables were included in our model.

1. ***Targeted return***: the percentage difference between the targeted selling price (TSP) for buy recommendations and the market price at that time[9].
   Several authors have look at price aggressiveness or price premium as an important factor in the execution of limit orders in market microstructure studies (see Al-Suhaibani and Kryzanowski (2000); Bessembinder et al. (2009) and Chatterjee and Mukhopadhyay (2013)). In this study, targeted return is a proxy for analyst optimism (or pessimism) for a particular stock. It is a continuous indicator of the strength of the recommendation

[8] http://www.indianotes.com/all-articles.php?type=VGVjaG5pY2FsX1N0cmF0ZWd5

[9] Glezakos and Merika had used the target price to classify the recommendations into the discrete categories denoted in I/B/E/S dataset. Instead we have created a continuous numerical variable called targeted return which is a proxy for the analyst optimism and is taken as one of the explanatory variables in the models.

captured by discrete categories such as "strong buy", "buy" "hold", "sell" and "strong sell" in the I/B/E/S database. We expect that higher targeted returns (greater price aggressiveness) will result in longer fulfilment times.

2. ***Average volume***: daily volume of trades in the stock in the pre-recommendation period.
   The average daily volume of trades is a proxy for investors' interest in and the liquidity of the stock. Several studies including Blume et al. (1994), Krische and Lee (2000), Jegadeesh et al. (2004) and Jegadeesh and Kim (2006) have looked at the effect of trading volume on the efficacy of analyst recommendations. It is expected that higher values of average volume indicates greater liquidity and the time to reach the target price will be smaller for stocks with greater liquidity. Hence we hypothesize a negative relation between average volume and time to fulfilment.

3. ***Beta***: computed beta for the stock in the pre-recommendation period (90 days).
   The effect of stock beta on the efficacy of analyst recommendations has been investigated in some empirical studies such as Andersson and Eriksson (2013), Hsu et al. (2013) Sayed and Chakladar (2014) and Kothari et al. (2016). Beta measures the correlation of the stock with the market return. Higher values of beta indicate the systematic risk in the stock returns. It is expected that as volatility increases, the analyst's ability to effectively predict the price movement will decrease. Hence we hypothesize that for higher beta stocks will result in poorer prediction accuracy resulting in higher time to fulfilment.

4. ***Market sentiment***: trend component of Sensex in pre-recommendation period (90 days).
   This is the slope coefficient computed by regressing the Sensex time series for the last six months with time. In our sample, the value of market trend varies from 1.08 to 1.71; i.e the data recorded showed mostly saw bullish runs. A large positive number indicates a strong bullish trend while a large negative number would indicate a strong bearish trend, etc. Qian (2009) and Bagnoli et al. (2010) investigated the relationship between market sentiment and analyst recommendations. They found that analysts often follow bullish trends; however such market sentiments do not necessarily result in accurate forecasts. We hypothesize that a bullish market sentiment will result in somewhat poorer prediction accuracy.

5. ***Sector***: a categorical variable (7 groups) indicating the industrial sector for a stock.

   This variable has been included to see whether the analysts are able to predict the prices of any particular industry stocks more accurately than others.

6. ***Market Movement***: Measure of the Sensex movement in the same observation window (in the case that the target price was reached).
   If the target price was reached within the observation window, that may due to the fact that the analyst's prediction was accurate or that there was significant movement in the market overall. Hence we need to control for the market movement factor to understand the true predictive content in the analyst recommendation. Thus, the market movement variable was included not as a predictive variable but as a control variable to avoid omitted variable bias in the estimation of the coefficients of the other variables.

Results

Descriptive Analysis

We present here some basic descriptive analysis of the data, within two observation windows, viz. 7 days after the recommendation and 30 days after the recommendation.

Buy vs. Sell

The target price was reached for only 18% of both buy and sell recommendations within the first week. If one waited for a month, then the target price was reached for about 43% of buy recommendations and 40% of sell recommendations, as can be seen from Table 1.

Table 1: Success Rates by Type of Recommendation (Buy vs. Sell)

	Target Price Reached within 7 days			**Target Price Reached within 30 days**		
Recommendation	0	1	% Success	0	1	% Success
Buy	213	46	18%	147	112	43%
Sell	106	25	19%	79	52	40%

Stock Recommender Performance

The largest number of recommendations in our sample was from HDFC Securities followed by Reliance Securities and Nirmal Bang (see Table 2). Amongst the recommendation sources with larger number of recommendations, Indiainfoline seems to have the highest success rate (36% within a week and 58% within a month). Reliance Securities has the next most successful performance record with 29% success rate within a week and 48% success rate within a month. Jainam Research did have an impressive success rate of 67%, but this was out of only 3 recommendations included in our sample.

Table 2: Success Rates by Stock Recommender

		Target Price Reached in 7 days			**Target Price Reached in 30 days**		
Analyst	**Total**	**0**	**1**	**% Success**	**0**	**1**	**% Success**
HDFC Sec	132	113	19	14%	76	56	42%
Reliance Securities	84	60	24	29%	44	40	48%
Nirmal Bang	66	59	7	11%	41	25	38%
Indiainfoline	36	23	13	36%	15	21	58%
SPA securities	20	19	1	5%	12	8	40%
Way2wealth	19	19	0	0%	19	0	0%
Rushabh Shastri	15	11	4	27%	9	6	40%
IFIN	11	11	0	0%	7	4	36%
Karvy	4	3	1	25%	2	2	50%
Jainam Research	3	1	2	67%	1	2	67%

Different Industrial Sectors

Most of the firms included in this study are from the Manufacturing sector, followed by Banking and Finance and then Metal, Oil and Power sector as can be seen from Table 3. In a seven day window, analyst's predictions were most accurate for firms in the Real Estate and Infrastructure sector followed by Telecom and Banking and Finance. The FMCG and Metal, Oil and Power sectors saw the lowest predictive ability from the analysts.

Table 3: Success Rates by Industry Sector

		Target Price Reached within 7 days			Target Price Reached within 30 days		
Industry Sector	**Total Number**	**0**	**1**	**% Success**	**0**	**1**	**% Success**
Manufacturing	98	80	18	18%	63	35	36%
Banking and Finance	79	62	17	22%	44	35	44%
Metal, Oil and Power	77	67	10	13%	42	35	45%
Healthcare	53	43	10	19%	30	23	43%
IT	30	25	5	17%	17	13	43%
Real Estate and Infrastructure	25	19	6	24%	16	9	36%
FMCG	15	13	2	13%	9	6	40%
Telecom	13	10	3	23%	5	8	62%

Non-Parametric Kaplan Meier plots

Non-parametric survival plots were plotted for both “buy” and “sell” recommendations. In the Kaplan Meier (K-M) plots, time is plotted on the x-axis while the probability of survival (i.e. the probability that the event has not yet happened) is plotted on the y-axis. The survival probability at time t=0 is 1. Hence the KM plot starts at 1 on the y-axis. Using actual event times (in this case the time at which a target price for a particular recommendation was reached), a decreasing step function indicates the probability of survival at each subsequent instant of time. The KM plot for our data for both buy and sell recommendations is given in Figure 1.

We find that the probability of the target price *not* being reached (in this case survival indicates that the target price was not reached) was about 60% for both buy and sell recommendations. However the KM curve for sell recommendations indicates a smaller probability of survival of sell recommendations compared to buy recommendations within the first 15 days. This indicates that the sell recommendations were typically more accurate at least within a window of the first 15 days after the recommendation. This finding along with the fact that there are typically more "buy" recommendations than "sell recommendation" confirms the optimism bias among analysts found by other researchers. Analysts do not like to issue "sell" recommendations, but when they do, it is possibly more accurate than "buy" recommendations (Bildstein-Hagberg, 2003).

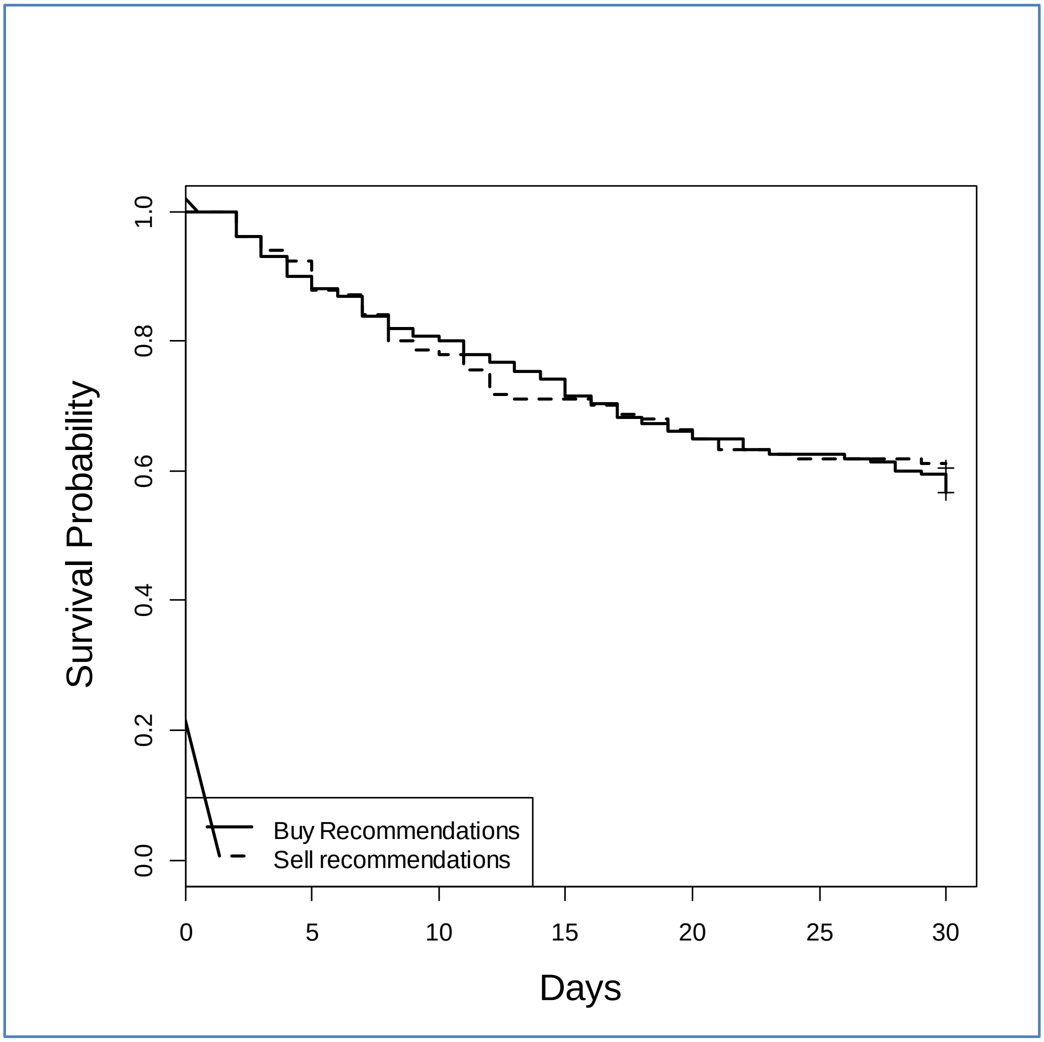

Figure 1: Kaplan Meier Survival Plot for All Buy & Sell Recommendations

Parametric Accelerated Failure Time Models

The Accelerated Failure Time (AFT) survival model for the Weibull distribution is given by the following equation:

$$S(t) = \exp\{-(\lambda t)^p\}$$

where $S(t)$ = probability of survival of the recommendation (i.e. probability target price will not be reached) at time t

λ = positive scale parameter[10]

p = shape parameter[11]

[10] $\lambda = (\frac{1}{\exp(\beta_0+\beta_1 X_1+\cdots+\beta_n X_n)})^p$ = scale factor that accelerates the time to fulfillment, given covariates X_1, X_2, ...X_n

[11] p>1 indicates monotonically increasing hazard rate with time, p<1 indicates monotonically decreasing hazard rate, p=1 indicates constant hazard rate with time.

We built several AFT models to estimate whether certain exogenous variables which measured stock-related and market-related factors (as described above) had statistically significant effects on the time taken for the stock price to reach the targeted (selling/buying) price. Several different probability distribution functions were used to model the survival times including (Gaussian, Exponential, Logistic, Weibull, Loglogistic and Lognormal). After comparing the AICs of the different models, it was found that the Weibull distribution yielded the smallest values of AIC (note Appendix II). The results of 7 Weibull models, with different sets of dependent variables have been tabulated in Table 4.

Discussion of Results of AFT Models

We see from Table 4, that Model 4 has the lowest AIC value of 1108.95 indicating that it has the best fit among all the models. In this model, the following three independent variables that have a statistically significant effect on the time taken for the target buying/selling price to be reached.

- Targeted Return: this has a positive coefficient indicating that as the targeted return is higher, the time taken for the target price to be reached is also greater. This makes sense intuitively and this effect has been found in other empirical studies. In fact since the coefficient of TR is 0.862, the expected time of reaching targeted price increases by a factor of $e^{0.862}$ or 2.368 times for each percentage rise in targeted return.
- Market Trend (bullish): this variable also has a statistically significant and positive effect on the time taken to reach the target price. If the market was bullish in the period before the recommendation, the analyst may expect it to continue in the same way. However, given the tendency of reversion to mean, this expectation may not be accurate. The beta coefficient of 0.660 indicates that with an increase of about 0.1 in the market trend would increase the time to reach target price by about 19.35%.
- Log of average volume of trades in the stock has a negative effect on the time taken to reach the target price. This is as expected - larger average volume of trades indicates a more liquid stock and the targeted price would be reached sooner in such stocks. An increase of about 3 units in the average volume of trades in the pre-recommendation period results in an 8% decrease in the time taken to reach the target price.

Other than these three variables, we find that in Model 7 (which has a higher reported AIC value), some of the industrial sectors have a statistically significant effect on the time taken to reach the target price. The reference category is Banking and Finance. We find that stocks belonging to the FMCG sector take a longer time in reaching the target price, while the stocks belonging to the Real estate and Infrastructure sector take a smaller time to fulfilment.

One important point to note is that the variable Market Movement which has been included in Models 2 through 6 improves the goodness of fit of the models (lower AIC). However, this variable is not statistically significant itself. It just helps to control for omitted variable bias in the coefficient for Targeted Return.

Table 4: Results of AFT Models for Recommendations Based on Technical Analysis - using Weibull Distribution

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Value	**P**	**Value**	**p**	**Value**	**P**	**Value**	**p**	**Value**	**p**	**Value**	**p**	**Value**	**p**
(Intercept)	3.681	0	2.524	0.000	1.706	0.000	2.681	0.000	2.727	0.000	2.704	0.000	2.280	0.001
Targeted Return	3.007	5.64E-15	0.929	0.012	0.870	0.021	0.862	0.020	0.872	0.021	0.863	0.021	1.121	0.002
Market Movement			1.354	0.226	1.284	0.242	0.531	0.647	0.514	0.657	0.426	0.720	1.730	0.177
Market Trend					0.647	0.075	0.660	0.067	0.655	0.070	0.640	0.078	0.667	0.051
log(Average Volume)							-0.080	0.052	-0.085	0.062	-0.082	0.082	-0.070	0.126
Beta									0.028	0.786	0.037	0.726	0.127	0.173
Sell Recommendation *											-0.045	0.720	0.100	0.436
Sector - FMCG **													0.789	0.006
Sector - Healthcare **													0.160	0.354
Sector - IT **													0.020	0.921
Sector - Manufacturing **													0.180	0.252
Sector - Metal, Oil and Power**													0.028	0.848
Sector - Real Estate & Infrastructure**													-0.452	0.058
Sector - Telecom**													-0.033	0.892
Log(scale)	-0.018	0.802	-0.416	0.000	-0.428	0.000	-0.440	0.000	-0.440	0.000	-0.441	0.000	-0.498	0.000
Loglikelihood	-796.459		-552.018		-550.348		-548.473		-548.437		-548.373		-541.457	
AIC	1598.918		1112.036		1110.695		1108.946		1110.874		1112.746		1112.915	

* This is a dummy variable that took values of 1 if the recommendation was a sell recommendation and 0 if it was a buy recommendation.

** The reference industry sector is Banking and Finance. The positive and statistically significant coefficient for FMCG sector indicates that the recommendations for FMCG stocks take more time to reach the target price than recommendations for Banking and Finance Sector stocks. Similarly the negative coefficient for Real Estate & Infrastructure stocks indicates that these recommendations reach the target price quicker than Banking and Finance stocks.

Conclusion

Most studies that have analysed the efficacy of analyst recommendations have analysed the abnormal excess returns generated through these recommendations compared to some benchmark strategy. Many of these studies have looked at recommendations classified into five different discrete categories - viz. "strong buy" "buy, "hold", "sell" and strong sell". In the recommendations we looked at in this study, the analyst specified an action (buy/sell) and also a target selling price/buying price. Given the current market price of the stock at the time of recommendation and the target price, a targeted return was calculated for each recommendation. This variable was a continuous indicator of the strength of the recommendation or a measure of the analyst optimism.

In this study, since we are concerned with the liquidity of the trading advice (rather than the returns generated), the event of interest is the stock reaching the targeted price. Using archival data on stock prices after the recommendation date, we try to analyse the probability of the event occurring within a specific window (30 days) using survival analysis techniques. In our models, targeted return is an exogenous variable along with some other stock and market indicators. Thus this study is different from the existent studies in that we look at *liquidity* as opposed to *returns* and we use a continuous measure of analyst optimism rather than the discrete classes used by many other researchers.

Survival analysis models built for 403 technical calls indicate that a high targeted return (i.e. greater price aggressiveness) increase the time taken to reach the targeted price. This matches our intuition. A bullish market trend in the pre-recommendation period also increases the time to reach the targeted price. This can be intuitively explained when we see that a bullish trend may generate greater optimism in the analyst and the market may self-correct leading to the recommendations not being fulfilled. A high volume of trade in the pre-recommendation period, which is a proxy for the liquidity of the stock, reduces the time taken for fulfilment. In our sample, we find that compared to Banking and Finance sector stocks, Real Estate and Infrastructure stocks take a smaller time to reach the targeted price while FMCG sector stocks take a longer time.

The contribution of this study to the literature on analyst recommendation is threefold. First, it addresses the question of liquidity as opposed to returns, second it uses a continuous measure for analyst optimism as opposed to discrete categories such as "strong buy" etc. and finally it uses the different empirical methodology of survival analysis. High targeted returns and the presence of a bullish trend in the market prior to the recommendations reduces the efficacy of the recommendation while a greater liquidity of the recommended stock tends to increase the efficacy. This study confirms the findings of several other studies that recommendations for highly traded (or glamour) stocks seem to get executed soon. Overall, in keeping with the findings of several other studies, we find that analyst recommendations do not lead to trading strategies that yield high returns within a short period of time. This confirms the idea of weak form efficiency of the Indian stock market.

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Appendix I

Example of Recommendation based on Technical Analysis

TECHNICAL CALL

NIRMAL BANG
a relationship beyond broking

28 March 2016

2-3 DAYS

KTKBANK

DAILY CHART

CMP	: 102.4
Action	: Buy
Targets	: 108/112
Stop-loss	: 99
Duration	: 2-3 DAYS

Comment :
Momentum Indicator RSI showing a positive cross over in daily chart indicates strength in the stock is keeping a positive closing above the 6/30-DMA from two trading sessions Stock is showing strong signs.

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Appendix II

AIC Values for AFT Models Different Distributions for Time to Event - Technical Calls

		# Vars	AIC
GAIC0	Gaussian	15	1160.371
GAIC1	Gaussian	8	1157.582
GAIC2	Gaussian	7	1155.589
GAIC3	Gaussian	6	1153.735
GAIC4	Gaussian	5	1156.482
GAIC5	Gaussian	4	1157.677
GAIC6	Gaussian	3	1708.835
EAIC0	Exponential	14	1161.31
EAIC1	Exponential	7	1152.368
EAIC2	Exponential	6	1150.379
EAIC3	Exponential	5	1148.471
EAIC4	Exponential	4	1148.151
EAIC5	Exponential	3	1147.644
EAIC6	Exponential	2	1596.98
LAIC0	Logistic	15	1165.136
LAIC1	Logistic	8	1163.495
LAIC2	Logistic	7	1161.647
LAIC3	Logistic	6	1159.95
LAIC4	Logistic	5	1162.277
LAIC5	Logistic	4	1162.869
LAIC6	Logistic	3	1721.522

		# Vars	AIC
WAIC0	Weibull	15	1112.915
WAIC1	Weibull	8	1112.746
WAIC2	Weibull	7	1110.874
WAIC3	Weibull	6	1108.946
WAIC4	Weibull	5	1110.695
WAIC5	Weibull	4	1112.036
WAIC6	Weibull	3	1598.918
LLAIC0	LogLogistic	15	1137.04
LLAIC1	LogLogistic	8	1131.774
LLAIC2	LogLogistic	7	1130.068
LLAIC3	LogLogistic	6	1128.485
LLAIC4	LogLogistic	5	1129.661
LLAIC5	LogLogistic	4	1129.762
LLAIC6	LogLogistic	3	1575.192
LNAIC0	LogNormal	15	1130.279
LNAIC1	LogNormal	8	1122.522
LNAIC2	LogNormal	7	1120.587
LNAIC3	LogNormal	6	1118.885
LNAIC4	LogNormal	5	1119.603
LNAIC5	LogNormal	4	1119.972
LNAIC6	LogNormal	3	1571.118