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EXISTENCE AND EXPLOITABILITY OF FINANCIAL ANALYSTS' INFORMATIONAL LEADERSHIP

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Abstract: This paper bridges two recent studies on the role of analysts to provide new and relevant information to investors. On the one hand, the contribution of analysts to long-term price discovery on the US market is rather low. Considering earnings per share forecasts as the main output of analysts' reports, their information share amounts to only 4.6% on average. On the other hand, trading strategies set up on these EPS forecasts are quite profitable. Self-financing portfolios yield excess returns of more than 5% p.a. over the S&P 100 index for a time period of 36 years, which is persistent after controlling for the well-known risk factors. In this paper, we discuss the link between the low information shares and the high abnormal returns. We argue that information shares of analysts cannot be higher, because otherwise their forecasts would lead to excessively profitable trading strategies which are very unlikely to persist over such a long period of time.

Keywords: analysts, informational leadership, information shares, self-financing trading strategies.

1. Introduction

The importance of financial analysts working on the sell-side of the market, providing stock forecasts to a broad audience of market participants, remains controversial. As information intermediaries, their central functions are the identification, analysis, and aggregation of information which is new to investors and the effective communication of this information as a diversity of forecasts such as target prices, buy-sell-hold-recommendations, etc. With their knowledge of macroeconomic developments, markets, industry sectors and companies, financial analysts are expected to be in informational leadership relative to other stock market participants when it comes to assessing a firm's future development and its firm value. However, according to the efficient market hypothesis (EMH) of Fama (1970), the market itself is already efficient in processing new information. If the EMH holds, all relevant information is always fully reflected by stock prices and there is no economic legitimation for information intermediaries like financial analysts.

In this paper, we analyze the actual degree of informational leadership of sell-side financial analysts in developed stock markets and discuss the degree to which individual investors can profit from analysts' leadership. We first analyze the results of Baule and Wilke (2016), who employ a direct measure of analyst's informational leadership relative to other stock market participants and quantify the empirical information share of analysts' consensus forecasts of a company's earnings per share (EPS) in the price discovery process of US S&P 100 index members. These empirical information shares turn out to be very low and vary strongly in the cross-section. In fact, analysts seem to obtain informational advantages only for a relatively small number of companies. Based on these findings, we turn to the exploitability of potential informational advantages of analysts. We show that trading strategies based on a forecast-related mispricing measure, which is provided in Baule and Wilke (2015), yield exceptionally high risk-adjusted returns and are therefore highly profitable. Thus, although financial analysts have only very limited influence on the price discovery processes in highly developed markets, this small contribution to informational efficiency translates into potentially high abnormal returns when exploited by an appropriate trading strategy.

2. Analysts' Contribution to Long-Term Price Discovery

2.1 Informational Leadership in the Context of Financial Analysts and Stock Market Investors

Informational leadership in the context of financial analysts and stock market investors describes the ability of analysts to process new information faster than the investors and vice versa. Here, processing new information involves (i) identifying new information and (ii) interpreting new information. Certain parts of information are completely processed by analysts or investors at the moment they are reflected in analyst forecasts or stock prices. Wilke (2016) distinguishes between situations in which a party (analysts, investors) processes (i) at least a single information component faster (partial informational leadership), (ii) more than the half of relevant information faster (relative informational leadership) and finally (iii) all information available faster than the respective other party (absolute informational leadership).[1]

As stock prices and analyst forecasts are subject to noise and other non-informational movements, informational leadership analysis should not involve all changes in a company's stock or an analyst's forecast. In fact, it must separate information-driven permanent changes from transitory and information-free movements, which might be due e. g. to bid-ask bounces or individual investors' demand for liquidity. Stock prices and EPS forecasts tend to be non-stationary, which means that their distribution changes over time – this enables them to grow over all bounds. Non-stationary variables can be decomposed into a non-stationary component described by a stochastic trend and a stationary component. Information-driven movements are associated with the development of the non-stationary stochastic trend component, while information-free movements are connected to the stationary component, which does not influence the stock price or the EPS forecast in the long-run.

2.2 Information Shares – A Direct Measure of Analysts' Informational Leadership

Information shares as suggested by Hasbrouck (1995) provide a relative measure of informational leadership and are based on the concept of co-integration. Although

[1] See Wilke (2016), p. 73-75

non-stationary financial variables like stock prices or EPS forecasts might grow over all bounds, they tend to move together over time if they are co-integrated. Non-stationary variables are typically co-integrated, if they are driven by the same underlying fundamentals. Obviously, both stock prices and EPS forecasts related to a firm are driven by that firm’s fundamental development and are therefore expected to be co-integrated. Co-integration can be illustrated for (scaled) EPS forecasts and stock prices of Walt Disney (see Figure 1).

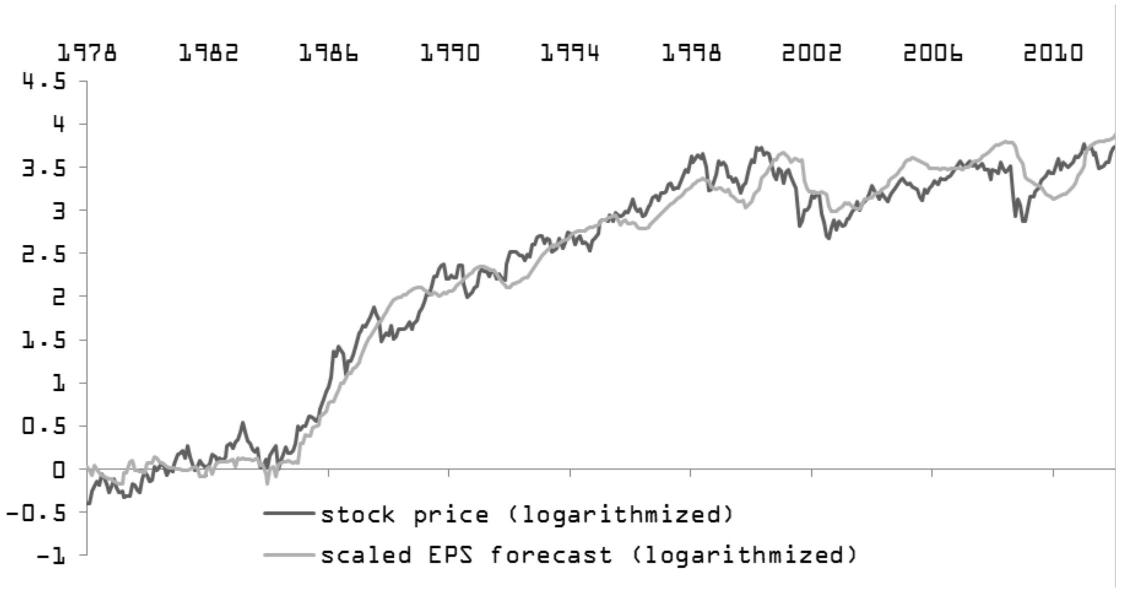

Figure 1: Co-movement of stock prices and (scaled) EPS forecasts for Walt Disney over time.

As Figure 1 shows, stock prices and (scaled) EPS forecasts develop stochastically over time. However, both series are fundamentally related, since both of them correspond to the fundamental value of the underlying company. This ties the development of prices and (scaled) forecasts together and makes them stay on a common long-term path. The common long-term path is characterized by the common stochastic trend shared by both time series. Information shares quantify the degree to which both prices and forecasts contribute to this common stochastic trend, and therefore to the common long-term development. The more EPS forecasts drive the common long-term development, the bigger is the information share of the analysts and – conversely – the lower the information share of the market participants.

2.3 Empirical Information Shares of Financial Analysts

Baule and Wilke (2016) compute empirical information shares for a highly liquid segment of the US American stock market. They analyze 75 constituents of the S&P 100 Index. The dataset is based on monthly data and spans 36 years, including monthly analyst consensus EPS forecasts and stock prices from January 1976 through March 2012. The analyst consensus forecasts are rolling twelve-month-ahead estimates. This means that every month’s EPS forecast estimates the development of the respective company’s earnings per share over the following one-year horizon. Market data are obtained from Thomson Reuters Datastream, forecast data are taken from the Thomson Reuters I/B/E/S database.

Table 1: Empirical information shares of financial analysts for S&P-100 Index members. Information shares significantly larger than zero are indicated by ° (10% level), * (5% level), ** (1% level) and * (0.1% level), based on bootstrapping methods.**

Name	$IS^{Analysts}$ (%)	Name	$IS^{Analysts}$ (%)
3M	1.1	IBM	3.3
Alcoa	0.7	Intel	0.3
Altria Group	33.3*	Johnson & Johnson	0.1
American Electric Power	0.2	JP Morgan Chase & Co.	10.1°
American Express	0.0	Kraft Foods	6.5
Apache	0.0	Lockheed Martin	0.0
AT&T	0.2	Lowe's	2.5
Avon Products	0.7	McDonald's	1.6
Baker Hughes	2.4	Medtronic	0.0
Bank of America	0.0	Merck & Co.	0.0
Bank of New York	0.0	Monsanto	1.2
Baxter International	0.0	Morgan Stanley	4.3
Boeing	0.4	National Oilwell Varco	1.3
Bristol-Myers Squibb	0.0	Nike	5.1
Caterpillar	1.5	Norfolk Southern Railway	27.5*
Chevron Corporation	2.3	Occidental Petroleum	0.0
Citigroup	23.6	Oracle	0.0
Coca-Coal Company	0.0	PepsiCo	6.2
Colgate-Palmolive	0.0	Pfizer	0.0
ConocoPhillips	2.1	Procter & Gamble	0.0
CVS Caremark	2.6	Qualcomm	0.0
Dell	0.0	Raytheon	21.8*
Devon Energy	0.0	Schlumberger	0.8
Dow Chemicals	0.0	Southern Company	0.4
Emerson	5.0	Sprint Nextel	22.3*
Entergy	5.4	Target Corporation	7.5*
Exelon	7.3	Texas Instruments	0.0
Exxon Mobil	0.0	Union Pacific	15.2*
FedEx	12.9°	United Technologies Corp.	15.7*
Freeport-McMoRan	0.0	UnitedHealth	0.1
General Dynamics	13.4*	US Bancorp	0.0
General Electric	0.0	Verizon Communications	0.2
Gilead Sciences	8.8	Walt Disney	9.5°
Halliburton	0.0	Wells Fargo	15.7*
Heinz Company	0.0	Weyerhaeuser	29.1**
Hewlett-Packard	3.4	Williams Companies	0.0
Home Depot	0.0	Xerox	0.0
Honeywell International	6.9		
Mean	**4.6*** **	**Min**	**0.0**
SD (Mean)	**7.7**	1Q	0.0
SE (Mean)	**0.9**	Median	0.7
		3Q	6.2
		Max	**33.3**
Companies	**75**		
Significance at 10% level	**13**		
Significance at 5% level	**9**		
Significance at 1% level	**1**		

Table 1 shows the empirical information shares of financial analysts at the firm level. Obviously, most information is processed faster by the market itself than by financial analysts. Market prices reflect more than 95% of relevant information before they get incorporated into analyst consensus EPS forecasts. For the majority of the analyzed sample firms, investors are in absolute informational leadership compared to financial analysts. On average, the informational advantage of analysts is rather marginal; their share in price discovery is only 4.6%. Moreover, the analyst share varies considerably in the cross-section: For the broad majority of the examined firms, analysts possess no significant informational advantage at all. For single companies like Altria Group (33.3%), Norfolk Southern Railway (27.5%), Sprint Nexel (22.3%) or Weyerhaeuser (29.1%) however, analyst forecasts reflect a measurable and significant share of relevant information first. Only 13 out of 75 sample companies yield significant information shares for the analyst side. For these firms, analysts are in partial informational leadership and participate measurably in the price discovery process. Overall however, analysts appear to be pure information followers most of the time, contributing only to the price discovery process of a rather small number of firms.

3. Exploitability of Analysts' Informational Leadership

3.1 Informational Leadership in the Context of Financial Analysts and Stock Market Investors

As shown in the previous section, empirical information shares, which provide a direct measure of analysts' informational leadership, are exceptionally low in highly developed market segments such as the S&P 100 index constituents. However, as analysts do significantly participate in the price discovery processes of single firms, we now turn to an investment and portfolio management perspective and analyze whether a stock market investor is able to exploit the small but existent informational advantages of analysts. Baule and Wilke (2015) construct a measure of a stock's temporary misevaluation, termed Q. This measure focuses on information-driven EPS forecast revisions of financial analysts, relative to the corresponding actual stock returns observed in the market. The aim of Q is to identify stocks which analysts implicitly consider as under- or overvalued – based on their forecast revision and the corresponding actual stock return. An upward revision of a company's EPS forecast can be interpreted as a signal that financial analysts expect the fundamental value of the company to be higher now than before. If the market directly reflects analysts' forecast revisions, a positive forecast revision should be associated with a positive actual stock return for the observed period of time.

Based on these ideas, Q is defined as the ratio of the gross EPS forecast revision and the corresponding gross stock return:

$$Q_t = \frac{1+r_t^A}{1+r_t^S} \tag{1}$$

with

$$r_t^A = \frac{\widehat{EPS}_t - \widehat{EPS}_{t-k}}{\widehat{EPS}_{t-k}} \tag{2}$$

and

$$r_t^S = \frac{S_t - S_{t-k}}{S_{t-k}} \tag{3}$$

$\widehat{EPS}_t$ is the consensus EPS forecast of analysts in time t, and S_t the corresponding stock price. The parameter k defines the length of the formation period in months, over which the observed stock returns and forecast revisions of analysts are compared. For this study, k is fixed at 6 months.

3.2 Implementation of Q-based Trading Strategies

How effective is the Q measure in identifying over- and undervalued stocks in the US stock market top segment, and do Q-based trading strategies outperform the market? Which Q-based returns correspond to the very low empirical information shares measured between 1976 and 2012? In this section, we will analyze the efficiency of Q and the performance of Q-based trading strategies involving the S&P 100 index members.

We analyzed the time period from February 1978 to December 2013, during which a total of 278 companies were constituents of the S&P 100 index for at least one month. The index composition is updated monthly. The main variables include monthly stock returns and the corresponding monthly EPS consensus forecast revisions of the analysts. Since sample firms might pay dividends, and since during the sample period capital increases or stock splits might occur, we use adjusted stock prices. Overall the sample data are basically the same as that used to compute the empirical information shares. Again, all company related data is provided by Thomson Reuters. For the calculation of risk-adjusted returns, monthly risk-free rates and monthly empirical risk factors suggested by Fama and French (1993), Fama and French (2015), and Carhart (1997) are employed, which are freely available in the Kenneth R. French Data Library.[2]

Since the index composition is adjusted on a monthly basis, the tradable stock universe contains only the actual S&P-100 index members on every trade date. Every month, Q is computed for all eligible stocks to determine their actual degree of misvaluation, before the stock universe is ordered by Q in decreasing order. Therefore, the first positions within the ordered stock universe are always occupied by stocks which analysts implicitly consider to be undervalued, while the last positions contain stocks which analysts see as overvalued. A quintile approach is then used to divide the stock universe into five equally weighted portfolios. In decreasing order, these quintile portfolios are then categorized as a High20 portfolio (positions 1 to 20), MidHigh20 portfolio (21 to 40), Mid20 portfolio (41 to 60), MidLow20 portfolio (61 to 80) or Low20 portfolio (81 to 100). The holding period for all quintile portfolios is the 1-month window between two consecutive EPS consensus forecasts. Based on the five quintile portfolios, we implement two self-financing trading strategies which (i) buy the High20 portfolio while short-selling the Low20 portfolio (High20 – Low20 strategy), or (ii) buy both the High20 and the MidHigh20 portfolio while short-selling the MidLow20 and the Low20 portfolio (High40 – Low40 strategy). After every portfolio rebalancing, monthly quintile portfolio returns in excess of the risk-free rate and the returns of the two self-financing

[2] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

strategies are computed. The excess returns are calculated over the exact period between the day of the current portfolio reformation and the day of the consecutive portfolio revision.

3.3 Results and Discussion of the Q-based Strategies

Figure 2 shows cumulated excess returns for the High20 portfolio (black line) and the Low20 portfolio (grey line). Also included as a benchmark are the cumulated excess returns of the market (dotted line), i.e. the excess returns of the S&P-100 Index. The High20 portfolio clearly outperforms the market, while the Low20 portfolio underperforms.

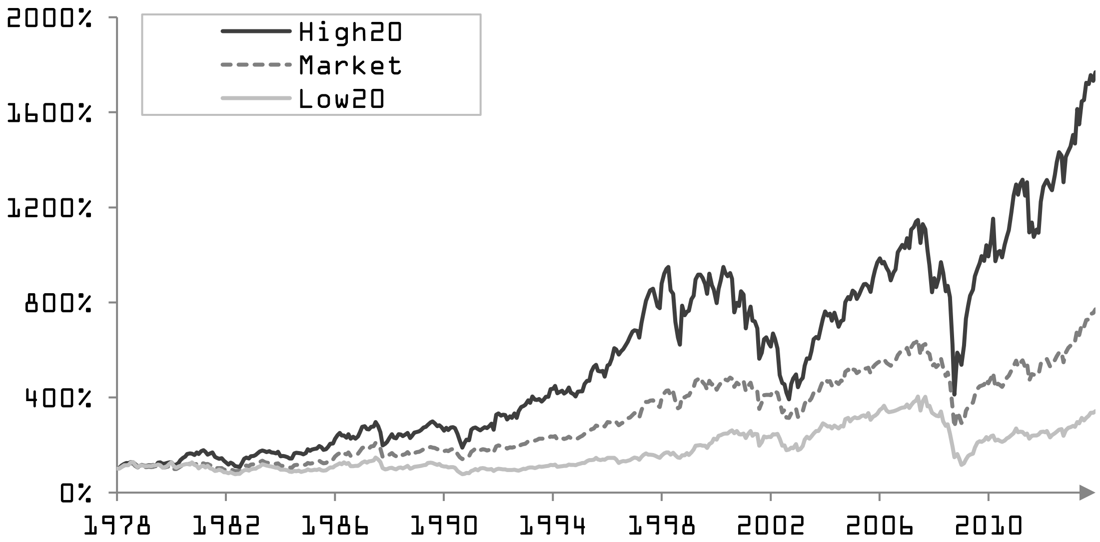

Figure 2: Performance of the Q-based extreme portfolios and the market.

Table 2 gives an overview over the performance of the quintile portfolios and the two self-financing strategies. Also included is the excess return of the market as a benchmark. Reported are monthly excess returns over the risk-free rate.

Table 2: Monthly excess returns of the Q-based quintile portfolios, the Q-based self-financing strategies and the market.

Portfolio	Mean excess return (%)	Std. Err. (%)
High20	0.886 **	0.317
MidHigh20	0.612 *	0.252
Mid20	0.571 **	0.218
MidLow20	0.494 *	0.221
Low20	0.439 °	0.263
S&P-100 Index (Market)	0.598 *	0.237
High20 – Low20	0.446 *	0.214
High40 – Low40	0.282 °	0.149

° $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The High20 portfolio yields monthly excess returns of 0.89%, the Low20 portfolio only 0.44%. Moreover, the mean excess returns decrease monotonically between both extreme portfolios. Obviously, Q is capable of identifying over- and undervalued stocks effectively. As a consequence, both self-financing strategies generate significantly positive returns: Buying the 20 (40) most undervalued stocks while short-selling the 20 (40) most overvalued stocks yields monthly returns of 0.45% (0.28%).

Figure 3 illustrates the development of the High20 – Low20 strategy returns within the analyzed period. Reported are both cumulated (black line, left axis) and not cumulated (grey bars, right axis) monthly strategy returns.

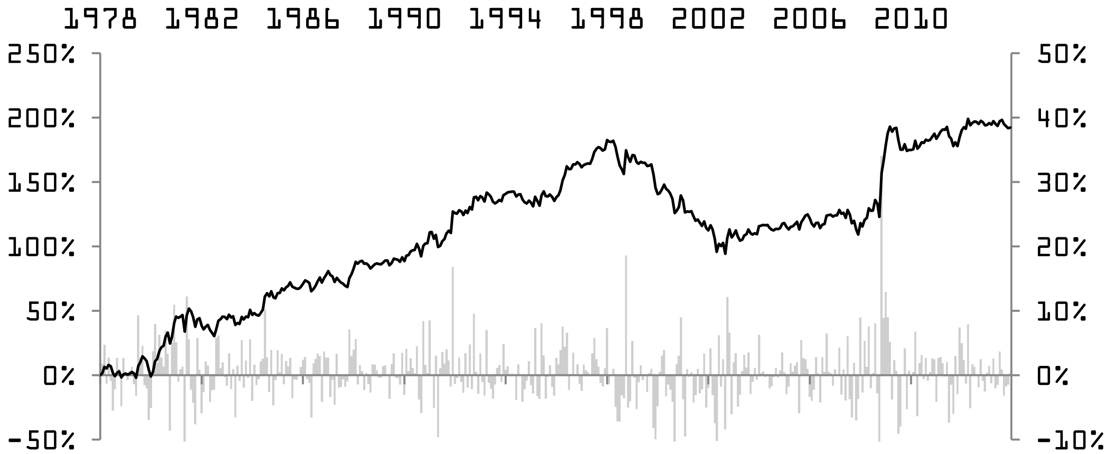

Figure 3: Performance of the Q-based extreme portfolios and the market.

Figure 3 shows that the Q-based strategy of buying undervalued stocks while short-selling overvalued stocks yielded positive monthly returns most of the time. However, analysts did not foresee the dotcom bubble, which was building up around the turn of millennium. Their informational advantage decreased significantly in the years between 1998 and 2002 and even turned into a relative informational disadvantage, which is reflected in the preponderantly negative returns throughout this period. In contrast, analysts were able to increase their informational edge in the turbulent first decade of the new millennium. Especially, they did not seem to lose their advantage in the course of the 2007 financial crisis. Indeed, the High20 – Low20 strategy generated an ongoing series of extremely high monthly returns in the recovery period around 2009. Overall, analysts seem to have withstood the decade’s turbulences better than the market.

3.4 Q-based Strategy Performance after Adjusting for Risk

The foregoing analysis concentrated on monthly returns in excess of the risk-free rate, which did not take into account that stocks differ in their risk-return characteristics. The observed high returns of the High20 portfolio might therefore simply be due to an increase in the riskiness of the portfolio investment. After all, are the discussed Q-based strategies systematically picking high-risk stocks to boost their performance? In the following, we therefore focus on risk-adjusted returns. We employ an empirical expansion of the CAPM which includes all well-established risk factors: the market factor (MKT), the two traditional Fama and French (1993) factors of firm size “small minus big” (SMB) and book-to-market ratio “high minus low” (HML), the Carhart (1997) momentum factor (MOM), and the two new Fama and French (2015) factors of profitability "robust minus weak" (RMW) and investment behavior "conservative minus aggressive" (CMA):

$$ER_t = \alpha + \beta_{MKT}\, MKT_t + \beta_{SMB}\, SMB_t + \beta_{HML}\, HML_t + \beta_{CMA}\, CMA_t + \beta_{RMW}\, RMW_t + \beta_{MOM}\, MOM_t + \varepsilon_t. \quad (4)$$

ER_t denotes the excess return of the Q-based portfolios over the risk-free rate in month t.

Table 3 shows the risk-adjusted performance of Q-based portfolios, based on the 6-factor model. The model fit is quite good, which is indicated by an adjusted R^2 ranging between 80% and 90% for the quintile portfolios. The portfolio alphas decrease significantly between both extreme quintile portfolios (High20, Low20). The High20 portfolio significantly outperforms the 6-factor model by 0.48% per month, while the Low20 portfolio gets outperformed by the model and yields a negative alpha of –0.22% per month. As a consequence, both self-financing strategies remain profitable even after adjusting for risk. The High20 – Low20 strategy generates a monthly alpha of 0.70% in excess of the 6-factor model; the High40 – Low40 strategy still outperforms the model by 0.49% per month. Notably, the High20 portfolio and the Low20 portfolio do not differ in terms of systematic market risk.

Table 3: Risk-adjusted performance of the Q-based quintile portfolios and the Q-based self-financing strategies.

n = 431	α	β_{MKT}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}	β_{MOM}	R^2
High	**+0.484*** (0.13)**	+1.081*** (0.35)	+0.199*** (0.05)	–0.046 (0.06)	–0.181° (0.09)	+0.030 (0.16)	–0.274 (0.04)	0.88
MidHigh20	**+0.035 (0.10)**	+1.017*** (0.03)	–0.088* (0.04)	–0.047 (0.05)	–0.038 (0.06)	–0.035 (0.05)	+0.030 (0.03)	0.90
Mid20	**–0.052 (0.08)**	+0.907*** (0.02)	–0.072* (0.04)	–0.037 (0.04)	+0.104° (0.06)	+0.077° (0.04)	+0.050* (0.02)	0.89
LowMid20	**–0.237** (0.09)**	+0.946*** (0.02)	–0.108** (0.04)	+0.039 (0.05)	+0.127* (0.06)	+0.107** (0.04)	+0.121*** (0.03)	0.88
Low20	**–0.215° (0.13)**	+1.017*** (0.04)	+0.060 (0.05)	+0.093 (0.07)	–0.022 (0.08)	–0.111* (0.06)	+0.094* (0.04)	0.82
High20–Low20	**+0.699*** (0.21)**	**+0.064 (0.07)**	**+0.139° (0.08)**	**–0.139 (0.12)**	**–0.159 (0.15)**	**+0.081 (0.10)**	**–0.368*** (0.07)**	**0.19**
High40–Low40	**+0.486*** (0.15)**	**+0.068 (0.05)**	**+0.079 (0.05)**	**–0.112 (0.06)**	**–0.162 (0.09)**	**–0.030 (0.07)**	**–0.230*** (0.05)**	**0.21**

4. Conclusion: Low Level of Informational Leadership but High Level of Exploitability

How do the results of low information shares and high abnormal returns relate to each other? In the first part of this paper we found that analysts exercised only marginal informational leadership on highly developed stock markets. On average, equity analysts tend to be information followers rather than information leaders. However, since analysts do possess temporary informational advantages for a small number of firms, they do take part in the price discovery process of the overall market. In the second part of the paper, we discussed the misvaluation measure Q as a vehicle to identify stocks which analysts implicitly consider over- or undervalued. The results show that Q is quite successful in determining the current level of a stock’s misvaluation. Putting both results together, individual investors could exploit analysts’ informational edges systematically and generate highly significant returns on their investment – even though the empirical informational leadership of analysts is relatively marginal.

Are these results implausible? Is the empirical information share of analysts “too small” or the corresponding individual profit “too high”? Neither one nor the other. If the information shares of analysts were considerably larger, they would be able to make much better predictions about stock market movements for mid-term investments, meaning we would observe even larger abnormal returns from trading strategies such as constructed by the Q measure. Much larger abnormal returns, however, are hardly likely to continue over such a long period of time. Thus, it is quite plausible that information shares of analysts are quite low, because otherwise obvious trading strategies following analysts’ EPS forecasts would lead to implausibly high abnormal returns.

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BOARD COMPOSITION AND INNOVATION

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Abstract: Corporate boards make key economic and financial decisions. Diversity in the boardroom, on one hand can lead to higher innovation by increasing interaction between heterogeneous agents; on the other hand it can lead to more conflict based on the predictions of social identity theory. In an examination of U.S. firms from 2000 to 2006, this study finds that board members' ascribed characteristics - gender, ethnicity, nationality, age; and acquired characteristics - education and experience are associated with higher innovation in form of patents and quality of innovation in form of citations.

Keywords: Corporate boards; Innovation.

1. Introduction

Recent socio-economic developments have put diversity in the spotlight. For example, the public press regularly bemoans the lack of ethnic and gender diversity in Silicon Valley.[1] Diversity is an important characteristic of corporate boards, benefits of which have been relatively under-examined in academic literature (Broome et al., 2011).[2] Thus far, the lens through which boards of directors have been looked at is board size and proportion of independent directors (Coles et al., 2007; Dennis and Sarin, 1999; Yermack, 1996; Anderson et al., 2000; Borokhovich et al., 1996; Mayers et al., 1997).[3] However, as Coles et al. (2007) point out - one size doesn't fit all and based on firms' business activity the board composition may vary. In this paper, we examine an important characteristic of corporate boards – diversity, and its effect on innovation.

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[1] https://www.theguardian.com/money/us-money-blog/2016/mar/06/silicon-valley-women-tech-industry-gender-pay-gap-bias
http://www.nytimes.com/2015/07/26/business/salesforce-makes-strides-toward-gender-equality-in-silicon-valley.html?_r=0
http://www.pbs.org/newshour/bb/how-silicon-valley-is-trying-to-fix-its-diversity-problem/

[2] Broome et al. (2011) interview corporate directors along the benefits of race and gender and generally discover that participants are reluctant to talk about these categories.

[3] Coles et al. (2007) find a U shaped relationship between board size and Tobin's Q.
Denis and Sarin (1999) show that board changes are strongly related to CEO turnover, past performance and threat from market for corporate control and weakly related to firm level factors such as stock return variance, size, leverage and growth opportunities. Yermack (1996) shows firms with small boards with more number of outside directors have higher market valuation. Anderson et al. (2000) also find a positive relationship between outside directors and firm value in diversified firms. Borokhovich et al. (1996) show that outside directors are associated with outside CEO replacement which is further associated with higher stock price returns. Mayers et al. (1997) also find outside directors are more efficient in mutual fund industry.

Schumpeter (1934) has called innovation as the engine of growth. Through innovation firms introduce novel products and processes that help them create new areas of profit or cut costs. Therefore, innovation keeps the businesses alive. However, Holmstrom (1989) defines innovation as risky, long-term and with high rates of failure. Corporate governance mechanisms, both internal and external, play a key role in determining the level and quality of innovation. Previous research looking at corporate governance and innovation has focused on the role of institutional investors (Aghion and Tirole, 2013): CEO incentives (Francis et al., 2016); market for corporate control (Seru, 2014); bank lending (Francis et al., 2012); shareholder rights (Sapra et al., 2014); and regulation (Shadab, 2008).

Corporate boards become relevant in the discussion about innovation because teams are much better at making risky decisions compared to individuals. Cooper and Kagel (2005) note that teams play more strategically and generate more positive synergies. Similarly, Rockenbach et al. (2007), and Blinder and Morgan (2005) study investment decisions by individuals and groups and find that groups make better decisions in terms of risk taking in uncertain environments than individuals. Kugler et al., (2012) conduct review of the literature on group decisions over past 25 years and find that results are widely consistent with rational decision making by groups. In context of innovation, diversity in groups becomes all the more important. Innovation is an interactive process and relies heavily on social cohesion (Lundvall, 1985, 92, 2002). Ostergaard et al., (2011) empirically show that employee diversity makes firms more innovative. A broader cultural and ethnic base leads to a greater knowledge base. Schumpeter (1934) asserts that a boarder knowledge base would produce more innovative ideas. Studies looking at diversity in top management teams also confirm the positive role of diversity in innovation (Williams and O'Reilly, 1998, ver der Vegt and Janssen, 2003; Woodman et al., 1993; Richard et al., 2004).[4] Because major economic decisions are made at the corporate board level, we concentrate on how diverse boards contribute to innovation.

To empirically test the effect of board composition on innovation, we gather data from four different sources – Boardex, RiskMetrics, NBER patent data project and Compustat. After matching these databases we are able to compile a sample of 5,432 U.S. firms spanning from 2000 to 2006. We measure innovation as the number of patents applied for by a firm in a given year. To capture the quality of innovation we use citations. More citations are associated with more radical innovation (Griliches et al., 1987; Hall et al., 2005). Following Ostergaard et al. (2011) and Ruef et al., (2003), we classify board diversity in form of ascribed and achieved characteristics of directors. Ascribed characteristics include gender, nationality, ethnicity, and age; and achieved characteristics include qualifications and experience.

We first look at ascribed characteristics. We find that male dominated boards have a negative relationship with patents. Further, a higher number of foreigners and non-Caucasian members on the corporate board is also associated with higher patents. In case of age, we look at the difference in ages of the oldest and youngest board member and we find that it has a positive relationship with patents. To determine the relationship between board characteristics and quality of innovation we look at their

[4] Williams and O'Reilly, 1998 provide a review of 80 studies over 40 of research on role of diversity in performance and creativity and provide mixed evidence. ver der Vegt and Janssen (2003) conduct a questionnaire study and find a strong correlation between innovation and task interdependence in heterogeneous teams. Woodman et al. (1993) develop a theoretical framework for organizational creativity and interaction.

impact on citations. Again gender has a negative impact, non-Caucasian and foreigners have a positive impact. Age range has a negative relationship with citations. Within the achieved characteristics we find that both education and experience have a positive impact on patents and citations. In general, we find that diversity is associated with higher innovation.

This paper contributes to the literature examining relationship between diversity and innovation in firms. The findings are consistent with those of Ostergaard et al., (2011), who find employee diversity brings in different points of view and adds to the interactive process of innovation.

In the next section we discuss our hypotheses, Section 3 provides an overview of the data, a description of variables and methodology. In Section 4 we discuss the results and conclude in Section 5.

2. Theoretical Background

2.1 Ascribed Characteristics: Gender, Nationality, Ethnicity, and Age

Gender Diversity: Extant research on risk taking behavior of women has mostly been consistent with risk avoidance (Bruce and Johnson, 1994; Hudgens and Fatkin, 1985; Sunden and Surette, 1998; Bernasek and Shwiff, 2001)[5]. However, other studies have shown evidence contrary to the stereotype that women are risk averse. For example, Barber (2001) and Huang (2008) show that men tend to be overconfident and make aggressive and risky decisions; Croson and Gneezy (2004) and Niederle and Vesterlund (2007) argue that women display risk aversion because they prefer less competitive situations; Johnson and Powell (1994) review the literature on male and female decision making and find no difference in risk taking of women, they, however, argue that stereotypes of women in non-managerial roles are imposed on women in managerial roles. Dwyer et al., (2002) suggest that the relationship between gender and risk taking may be a function of knowledge disparities. Weber and Zulehner (2010) show that startups with women have higher chances of survival. Adams and Funk (2011) look at gender differences in directors and find that female directors make more stakeholder oriented decisions but they are not necessarily risk averse. Adams and Ferreira (2009) show that female directors are also better monitors, although they document a negative relationship between gender diversity and firm performance. With already established gender differences in risk taking and economic decisions, gender differences should contribute to diverse points of view and hence should positively impact innovation.

National Cultural Diversity: Frijns et al., (2016) examine the role of national cultural diversity on corporate boards in determining firm outcomes. The authors find that national diversity has a negative relation with Tobin's Q. However, the authors find that the negative relationship disappears for complex firms with significant exposure to international markets. Their findings are consistent with Masulis et al. (2012) who show a negative effect of foreign directors on firm performance. In contrast, Estelyiova and Nisar (2016) show that foreign directors on boards are associated with better performance.

[5] Bruce and Johnson (1994) look at male and female betting behavior and find greater propensity for risk taking for men but better performance and confidence for women. Hudgens and Fatkin (1985) argue that gender differences occur when probably of success is low. Sunden and Surette (1998) also establish gender differences in investment portfolio decisions; Bernasek and Shwiff (2001) also find higher risk aversion in single womens' investment portfolio.

Ethnic Diversity: Ethnic diversity brings with it a broad spectrum of ideas in form of differences in attitudes, cognitive development, values and norms. Milliken and Martins (1996) argue that in small numbers ethnic diversity might be detrimental because minority groups may feel dissatisfied. However, on a larger scale, the benefits of new ideas and perspectives outweigh the costs and firms become more innovative. Richard (2000) further enforces the value of racial diversity. Richard et al., (2004) find a curvilinear relationship between cultural diversity and performance for high-risk firms. Richard et al., (2003) argue that racial diversity acts as a knowledge based resource and empirically show that racial diversity has a positive impact on performance only for innovative banks. The extant literature on the impact of racial and national cultural diversity on firm performance is mixed. We conjecture, because specifically innovation benefits from different points of views, its relationship with innovation should be positive.

Age Diversity: Studies on age have shown that younger employees are more innovative (Bantel and Jackson, 1989). Similarly, Wiersema and Bantel (1992) show that younger managers are more receptive to change and willing to more take risk. Compared to young executives, older executives have become more rigid as they age and avoid taking risks (Carlson & Karlsson, 1970; Vroom and Pahl, 1971; Taylor, 1975). Zajac et al., (1991) look at role of internal corporate joint ventures in enhancing innovation, and find that age similarity among members to be a critical factor. Younger boards, with similar age composition, therefore, should have a positive impact on innovation.

2.2 Achieved Characteristics: Qualification & Experience

Both experience and educational background have been documented to have a positive impact on firm performance. Cohen and Levinthal (1990) argue that a firm's investment in R&D is associated with role of diversity and expertise within an organization. Similarly, Murray (1989) shows that heterogeneous teams are more adaptive. Carpenter (2002) shows positive relationship between top management team heterogeneity and performance. The author captures heterogeneity in the form of education, functional experience and tenure. Finkelstien and Hambrick (1990) look at top management team tenure and find that it has a significant impact on corporate strategy and performance. Consistent with previous literature we should find experience and education to positively affect innovation.

3. Data and Methodology

3.1 Data

We obtain our data from three different sources. The information about board of directors comes from Boardex. Boardex is compiled by Management Diagnostic Corporation and contains biographic information about board members and executives. We use NBER patent data constructed by Hall et al., (2001) to get data on innovation. The authors have put together data on patents citations from United States Patent Office (USPTO) patent applications spanning the period 1963- 2006. Due to concerns regarding truncation bias in citations the authors also provide corrected citation data. We gather this data from NBER (see Hall et al., 2001, for details). We also obtain data on ethnicity of directors from RiskMetrics. Finally, we obtain financial and accounting information from Compustat.

We match firms in Boardex with other databases using ticker symbol and CUSIP derived from ISIN code. The patent data ends at 2006 and earliest year in Boardex is 1999. After matching Boardex with NBER patent database and Compustat we are able to create a sample from 2000 to 2006, with 5432 unique U.S. firms of which 1216 firms applied for a patent during the sample period.

3.2 Description of Variables

We measure innovation as count of patents applied for by a firm. Because count of patents is a discrete variable we take logarithm of count of patents (Log Patents). In order to measure quality of innovation we use forward citations as another dependent variable (Log Citations). Forward citations are the number of citations a patent receives in subsequent years. Hall et al., (2005) show a positive relationship between forward citations firm value. Patent data ends in 2006, therefore there is no measure of citations after 2006 which leads to a truncation bias in the dataset. Hall et al., (2001) provide a corrected measure of citations that addresses the truncation bias.[6] Thus we take logarithm of corrected citations as our measure for quality of innovation.

To capture board diversity we use several variables. We measure %Male as number of males divided by total number of directors on board. %Foreigners is ratio of total number of foreigners to total number of directors on board. %Non-Caucasian is the ratio of non-Caucasian directors divided by to total number of directors on board.[7] Age Range is the difference in age of the oldest and youngest director on the board. Average Education is average number of qualifications of the board members. Time in role is the average number of years as director on the board.

We also control for board and firm level factors that have been shown to affect firm outcomes. For example, Yermack (1996) and Fich and Shivdasani (2006) provide evidence that busy boards are detrimental to firm value. Coles et al. (2007) show that focused on R&D benefit from having fewer independent directors, which is also consistent with previous literature (Fama and Jensen, 1983; Klein, 1998). However, Director's networks have been shown to positively affect innovation (Faleye, 2009). Consequently, we include measures for board size and independence. Board size is total number of directors on the corporate board. %Independent is the ratio of total non-executive independent directors to board size.

Our control variables include Book leverage, which is defined as is total debt divided by total assets, ROA is defined as net income divided by total assets, R&D/TA is R&D divided by total assets. We also include R&D missing, which is a dummy variable that equals one if R&D is missing and Log assets is log of total assets. All our regressions include year and two-digit SIC industry level controls.

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[6] Hall et al. (2001) argue that due to the truncation of data, we do not observe citations beyond 2006. Further, citation intensities vary over time and industry classes. The authors use quasi-structural method, which allows for the separate identification of sources of variation related to time and cohorts. The NBER patent data file includes the corrected measure of patents using weights derived from the quasi-structural method. We use citations corrected using the quasi-structural method as our measure of the quality of innovation.

[7] The data on ethnicity comes from RiskMetrics, which categorizes director's ethnicity as Asian, African-American, Caucasian and Hispanic.

4. Results

4.1 Summary Statistics

Table 1 presents summary statistics for our key variables of interest. Out of 23,315 firm year observations we have patent data available for 3,891 firm years. On average, the firms in our sample applied for 34 patents and average citations received are 3,153. Book leverage is 22% and R&D/TA is at 5%. Average size of a firm in our sample is $7,457 million and ROA is -2%. Percentage of males in boards is about 93%, 5% of board members are foreign nationals, and 12% of board members are non-Caucasian. Average difference between the oldest and youngest board member is 25 years and board members have almost 2 qualifications.[8] The boards are almost 9 members in size and members have spent 6 years in their role as board members.

Table 1: This table presents the summary statistics of our variables of interest at firm level. Patents is total of number of patents applied for by the firm. Citations is number of corrected citations received. Board size is number of directors in the board. %Male is percentage of male members in the board. %Foreigners is percentage of foreign nationals in board. %Non-Caucasian is percentage of non-Caucasian directors on board. Age range is difference in ages of the oldest and youngest board member. Average age, is the average age of a director. Average education is number of qualifications. Board size is total number of directors on the board. % Independent is total Non-Executive Directors divided by total number directors. Time in Role is years spent as a director in the firm. Book Leverage is total debt divided by total assets. ROA is net income divided by total assets. R&D/TA is R&D divided by total assets. Assets is total assets.

	Mean	Median	5th Pctl	95th Pctl	#
Patents	33.68	3.00	1.00	123.00	3891
Citations	3153.45	50.40	0.00	9828.67	3891
%Male	92.60	100.00	75.03	100.00	22667
%Foreigners	0.05	0.00	0.00	0.32	15412
%Non-Caucasian	0.12	0.10	0.07	0.20	4819
Age Range	24.75	24.00	12.00	39.00	23283
Average Education	1.82	1.87	0.78	2.74	23035
Board Size	8.68	8.00	5.00	14.00	23282
%Independent	0.68	0.70	0.36	0.90	23315
Time in Role	5.88	5.33	1.48	11.98	23035
Book Leverage	0.22	0.17	0.00	0.64	23220
ROA	-0.02	0.03	-0.41	0.16	23289
R&D/TA	0.05	0.00	0.00	0.23	23315
Assets	7457.62	673.99	18.99	22284.90	23315

Table 2 shows board characteristics of patenting vs. non-patenting firms. Percentage of males in for patenting firms is slightly lower at 92% compared to non-patenting firms at 93%. Patenting firms also have larger number of foreign nationals. Ratio of foreign directors to board size for patenting firms is at 9% compared to non-patenting firms where it is 4%. There is no significant difference between ratio of non-Caucasian directors on boards, board size and percentage of independent directors of patenting versus non-patenting firms. The age range of directors for patenting firms is slightly lower than non-patenting firms. Directors in patenting firms have longer experience within the company (6.07 years, as compared to 5.83 years for non-patenting firms); they also have longer

[8] Average age of the board members is 58 years.

experience on other boards. R&D/TA for patenting firms is significantly higher and book leverage lower than their non-patenting counterparts.

4.2 Main Results

In this section, we look at the demographic composition of the board and its impact on innovation. Specifically, we look at the gender, nationality, ethnic, and age composition of the board. The results for these estimations are presented in Table 3.

Table 2: This table presents the T Tests of our variables of interest at firm level. %Male is percentage of male members in the board. %Foreigners is percentage of foreign nationals in board. %Non-Caucasian is percentage of Non-Caucasian directors on board. Age range is difference in ages of the oldest and youngest board member. Average age, is the average age of a director. Average education is number of qualifications. Board size is total number of directors on the board. % Independent is total Non-Executive Directors divided by total number directors. Time in Role is years spent as a director in the firm. Board size is number of directors in the board. ROA is net income divided by total assets. Book Leverage is total debt divided by total assets. R&D/TA is R&D divided by total assets. R&D missing is a dummy variable that equals one if R&D is missing. Assets is total assets.

	Mean	Median	5th Pctl	95th Pctl	#
Patents	33.68	3.00	1.00	123.00	3891
Citations	3153.45	50.40	0.00	9828.67	3891
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%Foreigners	0.05	0.00	0.00	0.32	15412
%Non-Caucasian	0.12	0.10	0.07	0.20	4819
Age Range	24.75	24.00	12.00	39.00	23283
Average Education	1.82	1.87	0.78	2.74	23035
Board Size	8.68	8.00	5.00	14.00	23282
%Independent	0.68	0.70	0.36	0.90	23315
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Book Leverage	0.22	0.17	0.00	0.64	23220
ROA	-0.02	0.03	-0.41	0.16	23289
R&D/TA	0.05	0.00	0.00	0.23	23315
Assets	7457.62	673.99	18.99	22284.90	23315

Column 1 of Table 3 shows the relationship between %Male and Log Patents. The coefficient on %Male is negative and significant. This implies that increasing the number of males on corporate board has a negative impact on innovation. Column 2 shows results for %Foreigners and Log Patents and the coefficient on nationality diversity is positive and significant, therefore increasing the number of foreigners on the board should have a positive impact on innovation. Column 3 shows results for %Non-Caucasian directors on the board, and coefficient is positive and significant. Finally, Column 4 shows the impact of Age Range on Log Patents, the coefficient on Age Range is negative and significant. Columns 5 through 8 show the impact diversity measures on citations. Again, gender diversity has a negative effect, nationality and ethnic diversity has a positive effect on innovation and director age diversity in company has a negative and significant effect on citations. These findings are crucial, because they show that diversity is integral to promoting innovation.

Table 3: This table presents the OLS regression results. Log Patents is log of total number of patents applied for by the firm. Log Citations is log of corrected citations received. Board size is number of directors in the board. %Male is percentage of male members in the board. %Foreigners is percentage of foreign nationals in board. %Non-Caucasian is percentage of Non-Caucasian directors on board. Age range is difference in ages of the oldest and youngest board member. Board size is total number of directors on the board. %Independent is total Non-Executive Directors divided by total number directors. Book Leverage is total debt divided by total assets. ROA is net income divided by total assets. R&D/TA is R&D divided by total assets. R&D missing is a dummy variable that equals one if R&D is missing. Log Assets is log of total assets. All estimations include year and two digit industry fixed effects. Standard errors clustered at firm level are reported in the bracket. The ***, **, *, and + marks denote statistical significance at the 0.1%, 1%, and 5% level respectively

	Log Patents 1	Log Patents 2	Log Patents 3	Log Patents 4	Log Citations 5	Log Citations 6	Log Citations 7	Log Citations 8
%Male	-0.003*** [0.001]				-0.005* [0.002]			
%Foreigners		0.520*** [0.141]				0.749** [0.253]		
%Non-Caucasian			0.664* [0.344]				1.143* [0.684]	
Age Range				-0.002* [0.001]				-0.004* [0.002]
Board Size	-0.105* [0.042]	-0.127* [0.057]	-0.028 [0.112]	-0.077* [0.043]	-0.312*** [0.082]	-0.348** [0.108]	-0.105 [0.210]	-0.260** [0.082]
%Independent	0.187** [0.064]	0.275** [0.084]	0.403* [0.195]	0.191** [0.062]	0.383** [0.126]	0.524** [0.164]	0.817* [0.363]	0.395** [0.123]
Book Leverage	-0.213*** [0.050]	-0.284*** [0.068]	-0.379* [0.149]	-0.207*** [0.050]	-0.453*** [0.101]	-0.563*** [0.139]	-1.197*** [0.290]	-0.443*** [0.098]
ROA	-0.021 [0.048]	0.059 [0.077]	0.273 [0.244]	-0.019 [0.046]	-0.128 [0.107]	-0.053 [0.169]	-0.017 [0.534]	-0.122 [0.102]
R&D/TA	0.459*** [0.126]	0.895*** [0.202]	2.937*** [0.641]	0.460*** [0.122]	0.680** [0.255]	1.518*** [0.405]	5.227*** [1.316]	0.684** [0.246]
R&D Missing	-0.275*** [0.026]	-0.345*** [0.036]	-0.437*** [0.090]	-0.270*** [0.026]	-0.485*** [0.051]	-0.635*** [0.070]	-0.786*** [0.165]	-0.475*** [0.050]
Log Assets	0.141*** [0.010]	0.183*** [0.015]	0.282*** [0.031]	0.143*** [0.010]	0.227*** [0.017]	0.298*** [0.024]	0.443*** [0.050]	0.230*** [0.017]
Intercept	1.113*** [0.246]	0.365* [0.208]	-0.975** [0.304]	0.748*** [0.203]	3.260*** [0.439]	2.081*** [0.371]	-0.238 [0.560]	2.735*** [0.358]
#	22,552	15,323	4,377	23,160	22,552	15,323	4,377	23,160
R-squared	0.329	0.369	0.489	0.328	0.278	0.312	0.423	0.278

Next, we follow the extant literature and look at achieved characteristics of board members such as qualification and experience. These results are presented in Table 4.

Column 1 of Table 4 looks at Average Education and the coefficient is also positive and significant. Column 2 looks at Time in Role and the coefficient is positive and significant. Columns 3 and 4 show the impact of these variables on citations. Again education and experience have a positive impact.

Table 4: This table presents the OLS regression results. Log Patents is log of total number of patents applied for by the firm. Log Citations is log of corrected citations received. Average education is number of qualifications. Time in Role is years spent as a director in the firm. Board size is total number of directors on the board. %Independent is total Non-Executive Directors divided by total number directors. Book Leverage is total debt divided by total assets. ROA is net income divided by total assets. R&D/TA is R&D divided by total assets. R&D missing is a dummy variable that equals one if R&D is missing. Log Assets is log of total assets. All estimations include year and two digit industry fixed effects. Standard errors clustered at firm level are reported in the bracket. The ***, **, *, and + marks denote statistical significance at the 0.1%, 1%, and 5% level respectively

	Log Patents	***Log Patents***	***Log Citations***	***Log Citations***
	1	**2**	**3**	**4**
Average Education	0.061***		0.104**	
	[0.017]		[0.034]	
Log(Time in Role)		0.041*		0.067*
		[0.017]		[0.034]
Board Size	-0.090*	-0.093*	-0.284***	-0.288***
	[0.041]	[0.042]	[0.080]	[0.081]
%Independent	0.186**	0.204**	0.381**	0.412***
	[0.064]	[0.063]	[0.125]	[0.124]
Book Leverage	-0.202***	-0.203***	-0.437***	-0.440***
	[0.050]	[0.050]	[0.099]	[0.100]
ROA	-0.009	-0.039	-0.11	-0.159
	[0.047]	[0.047]	[0.105]	[0.104]
R&D/TA	0.412***	0.458***	0.605*	0.683**
	[0.122]	[0.123]	[0.249]	[0.250]
R&D Missing	-0.269***	-0.276***	-0.472***	-0.485***
	[0.026]	[0.026]	[0.051]	[0.051]
Log Assets	0.140***	0.145***	0.224***	0.233***
	[0.010]	[0.010]	[0.017]	[0.017]
Intercept	0.643**	0.646**	2.556***	2.565***
	[0.203]	[0.200]	[0.359]	[0.355]
#	22,920	22,920	22,920	22,920
R-squared	0.329	0.329	0.278	0.278

We combine all the variables of interest in one regression and present the results in Table 5. Column 1 of Table 5 shows results for Log Patents and Column shows results for Log Citations. %Male has a negative impact on our measures of innovation, and %Foreigners and %Non-Caucasian has a positive impact. Age Range and Average Education lose their significance and our measure of experience (Time in Role) has a positive impact. These findings are largely consistent with our previous results and the highlight the importance of ascribed characteristics in motivating innovation.

Table 5: This table presents the OLS regression results. Log Patents is log of total number of patents applied for by the firm. Log Citations is log of corrected citations received. Board size is number of directors in the board. %Male is percentage of male members in the board. %Foreigners is percentage of foreign nationals in board. %Non-Caucasian is percentage of Non-Caucasian directors on board. Age range is difference in ages of the oldest and youngest board member. Average education is number of qualifications. Time in Role is years spent as a director in the firm. Board size is total number of directors on the board. %Independent is total Non-Executive Directors divided by total number directors. Book Leverage is total debt divided by total assets. ROA is net income divided by total assets. R&D/TA is R&D divided by total assets. R&D missing is a dummy variable that equals one if R&D is missing. Log Assets is log of total assets. All estimations include year and two digit industry fixed effects. Robust standard errors are reported in the bracket. The ***, **, *, and + marks denote statistical significance at the 0.1%, 1%, and 5% level respectively

	Log Patents	***Log Patents***
	1	**2**
%Male	-0.005*	-0.009*
	[0.002]	[0.005]
%Foreigners	0.674***	1.006**
	[0.172]	[0.370]
%Non-Caucasian	0.684*	1.534*
	[0.290]	[0.612]
Age Range	-0.001	-0.005
	[0.002]	[0.005]
Average Education	0.052	0.122
	[0.040]	[0.086]
Log(Time in Role)	0.167***	0.298***
	[0.038]	[0.082]
Board Size	-0.065	-0.191
	[0.084]	[0.179]
% Independent	0.423**	0.779**
	[0.141]	[0.277]
Book Leverage	-0.465***	-1.358***
	[0.108]	[0.233]
ROA	0.177	-0.402
	[0.222]	[0.509]
R&D/TA	2.597***	4.574***
	[0.517]	[1.133]
R&D Missing	-0.458***	-0.836***
	[0.057]	[0.125]
Log Assets	0.264***	0.413***
	[0.019]	[0.037]
Intercept	-0.680*	0.258
	[0.386]	[0.779]
#	3,743	3,743
R-squared	0.511	0.448

4.3 Robustness

In this section, we focus our attention again on gender, nationality and ethnic diversity. We look at changes in diversity scores. We create a dummy variable called %Male ↓Dummy, which equals 1 for negative changes in percentage of males and 0 otherwise. %Foreigner↑Dummy is a dummy variable, which equals 1 for positive changes in foreigners on boards and 0 otherwise. %Non-Caucasian↑Dummy is a dummy variable, which equals 1 for positive changes in non-Caucasians on boards and 0 otherwise. These results are presented in Table 6.

Table 6: This table presents the OLS regression results. Log Patents is log of total number of patents applied for by the firm. %Male↓Dummy is a dummy variable that equals one if the change in %Male is negative. %Male is percentage of male members in the board. %Foreigner↑Dummy is a dummy variable that equals 1 if change in %Foreigners positive. % Foreigners is percentage of foreign nationals in board. %Non-Caucasian↑Dummy is a dummy variable that equals 1 if change %Non-Caucasian is positive. %Non-Caucasian is percentage of Non-Caucasian directors on board. Board size is total number of directors on the board. %Independent is total Non-Executive Directors divided by total number directors. Book Leverage is total debt divided by total assets. ROA is net income divided by total assets. R&D/TA is R&D divided by total assets. R&D missing is a dummy variable that equals one if R&D is missing. Log Assets is log of total assets. All estimations include year and two digit industry fixed effects. Standard errors clustered at firm level are reported in the bracket. The ***, **, *, and + marks denote statistical significance at the 0.1%, 1%, and 5% level respectively

	Log Patents **1**	***Log Patents*** **2**	***Log Patents*** **3**
%Male↓Dummy	0.044**		
	[0.016]		
%Foreigner↑Dummy		0.125**	
		[0.047]	
%Non-Caucasian↑Dummy			0.229***
			[0.056]
Board Size	-0.103*	-0.099*	-0.105**
	[0.040]	[0.040]	[0.040]
%Independent	0.202**	0.209***	0.192**
	[0.062]	[0.062]	[0.062]
Book Leverage	-0.208***	-0.207***	-0.204***
	[0.049]	[0.049]	[0.049]
ROA	-0.017	-0.015	-0.012
	[0.046]	[0.046]	[0.046]
R&D/TA	0.462***	0.462***	0.462***
	[0.122]	[0.122]	[0.121]
R&D Missing	-0.271***	-0.271***	-0.269***
	[0.026]	[0.026]	[0.026]
Log Assets	0.143***	0.143***	0.140***
	[0.010]	[0.010]	[0.010]
Intercept	0.765***	0.757***	0.810***
	[0.204]	[0.203]	[0.202]
#	23,162	23,162	23,162
R-squared	0.328	0.329	0.33

Column 1 of Table 6 shows results for %Male↓Dummy regressed on Log Patents. We find that increases in women in corporate boards are associated with higher innovation. Similarly %Foreigner↑Dummy and %Non-Caucasian↑Dummy is also associated with higher innovation.

The findings in the paper support our initial predictions about a positive relation between gender, national culture and ethnic diversity on innovation.

5. Conclusion

We look at how diversity in form of ascribed and achieved characteristics of directors on the corporate board impact innovation. We find that ethnicity and nationality mix has a positive impact on innovation and age dissimilarity and lack of women has a negative impact. Qualifications and experience also contribute to higher innovation.

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MULTIDIMENSIONAL LIQUIDITY: EVIDENCE FROM THE INDIAN STOCK MARKET

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Abstract: Various dimensions of liquidity including breadth, depth, resiliency, tightness, immediacy are examined using BSE 500 and NIFTY 500 indices from Indian Equity market. Liquidity dynamics of the stock markets are examined using trading volume, trading probability, spread, Market Efficiency coefficient, and turnover rate as they gauge different dimensions of market liquidity. We provide evidences on the order of importance of these liquidity measures in the Indian stock market using machine learning tools like Artificial Neural Network (ANN) and Random Forest (RF). Findings reveal that liquidity variables collectively explain the movements of stock markets. Both these machine learning tools perform satisfactorily in terms of mean absolute percentage error. We also find a lower level of liquidity in the Bombay Stock Exchange (BSE) than the National Stock Exchange (NSE) and findings supports the liquidity enhancement program recently initiated by BSE.

Keywords: Liquidity, Turnover Rate, Market Efficiency Coefficient, Trading Probability, Artificial Neural Network, Random Forest.

1. Introduction

Liquidity is often explained as the ability to do large transactions, quickly, at low transactions costs and the evidences on the relation between liquidity and returns is important due to the fact that if liquidity affects returns, then from an investor's point of view liquidity risk needs to be priced. The most influential work on this front owes to Amihud and Mendelson (1986), who provide the first theoretical motivation establishing the relation between assets with low liquidity (or high transaction costs) and return premium. Their model was single-period with non-stochastic levels of liquidity. However, in multi-period models (Constantinides, 1986; Heaton & Lucas, 1996), it has been shown that cross-sectional differences in liquidity are not a pre-condition for a large premium on liquidity. There has been a resurgence of interest in the time-series dynamics of liquidity as well as the impact of the level of liquidity and liquidity risk on expected returns and, in turn, the cost of capital. An important observation about liquidity is that it is a parameter often endogenous to the environment. The interaction between investors' buying and selling decisions determines liquidity in equilibrium. Given the endogeneity of liquidity, it is of particular interest to explore the nexus between financial market movements and time-series movements in liquidity.

Liquidity is one of the imperative characteristics of a financial market and is considerably important for investment plans and financial assets. It probably does not have a single universally accepted definition. It changes with asset class and type of markets. Even within various financial markets, liquidity is empirically characterized in terms of breadth, depth, and resilience, often along with tightness and immediacy. The liquidity of major world financial markets substantially varies over time. Thus the unpredictability of market liquidity thereby is an important source of risk for investors.

In 1996 the NSE was set up, but other institutions and regulations facilitating trade like clearing corporations, depository and dematerialization, elimination of badla - a charge, which the investor pays for carrying forward his position, rolling settlement, ETF and derivatives trading through NSE were set up subsequently. Additionally, post 2000 we experienced events like the IT boom, stock market scams and World recession due to global financial crises. It would be interesting to see how liquidity has changed over time after these developments and events. The goal of this paper is to explore whether the Indian Stock market is related to its endogenous liquidity measures. We test for liquidity in terms of market depth, breadth, and resilience by using different liquidity measures that are deemed appropriate for equity market.

The next section provides some details on machine learning tools used in this study and in section 3 we present the previous research on similar and allied topics. In section 4 and 5 we discuss the data and methodology. In section 6, we discuss the findings and analysis and in section 7 we present our conclusion.

2. Machine learning Tools: Artificial Neural Networks and Random Forest

During last few years there has been much advancement in the application of machine learning algorithms in stock market index forecasting, endeavouring extraction of patterns in the market. Patel et al. (2015) and Wu and Lee (2015) provide a good summary of the work done in this field. Their work highlights the limitations of traditional statistical models including moving average, exponential smoothing, and ARIMA models which are linear in their predictions of the future values. From a statistical point of view, Artificial Neural Networks (ANNs) are analogous to nonparametric, nonlinear, regression models. However, the traditional statistical models have limitations in understanding the relationship between the input and the output of the system, especially when the system shows chaotic behaviour and is complex. Another machine learning algorithm which has been found to be good at such predictions is Random Forest. Theofilatos et al. (2012) apply five learning classification techniques (K-Nearest Neighbours algorithm, Naïve Bayesian Classifier, Artificial Neural Networks, Support Vector Machines and Random Forests) and observe that techniques like Support Vector Machines and Random Forests clearly outperform all other strategies in terms of annualized return and Sharpe ratio. Qin et al. (2013) applied the Random Forest method (Gradient Boosted Random Forest) as a nonlinear trading model to the stock market return of Singapore stock exchange and suggested that the proposed trading methods outperformed buy and hold strategy for similar period.

2.1 Artificial Neural Network (ANN)

ANNs are data driven models which can be used for non-linear natural real world systems while linear models generally fail to understand the data pattern and analyze when the underlying system is a nonlinear one. While some parametric nonlinear model such as ARCH and GARCH models have been in use for financial forecasting, most of such nonlinear statistical techniques require that the nonlinear model be specified before the estimation of the parameters is done. This requirement limits such models, as it generally happens that pre-specified nonlinear models may fail to observe the critical features of the complex system under study. ANNs are able to independently learn the relations inherent in the input data and discover nonlinear relations in the input data set without a priori assumptions about the relation between the input and the output.

ANN is a massively parallel distributed processor made up of a simple processing unit which has a natural propensity for storing experiential knowledge and making it available for use (Haykin, 1999). They are composed of one or more hidden layers sandwiched between the input and the output layers. Each layers is made up of a given number of nodes, and in case of a simple Feed Forward Multi-Layer Perceptron (MLP) ANN, each node in a given layer is connected to the ones in the next layer by arcs knows as synapses, taking cue from biological neurons in our bodies which are connected to each other and accept electrical charges across synapses. The input layer will have as many nodes as predictor variables (which takes in the input values to the network), and the output layer will have one node for estimation models (providing the output value) or for binary classification models (providing the probability for one of the output classes). In case of multiple (more than two) output classes, the output layer will have one node for each possible output class. The hidden layers can have any given number of layers with any given number of nodes in each of them. An illustrative ANN with two hidden layers of 3 nodes each, four input nodes and one output node is shown in Figure 1.

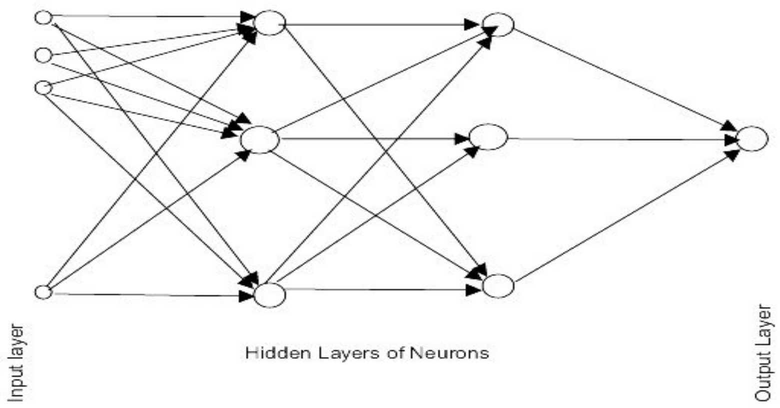

Figure 1: ANN with two hidden layers

Each arc in the network is assigned certain weight w. As an arc connects node i and node j, the value from node i gets multiplied with the corresponding weigh of the arc while traversing the concerned arc. Each node j (except those in the input layer of the ANN) also has some constant bias θj, which gets added up with the inputs received at node j; the output of node j being a function of these:

$$g(s) = g(\theta_j + \textstyle\sum_{i=1}^{p} w_{i,j} x_i). \quad (1)$$

The function g(s), known as the activation function, can be a linear, exponential, or a sigmoidal function. It can be the same function at each node in the network, or there can be different activation function, say sigmoid, at the hidden nodes, and say linear, at the output node(s). During the training phase of the ANN, the network is trained in terms of deciding on the weights wi,j and the biases θj, for every i, j, so that the network can provide the desired output.

One of the learning techniques used in MLP ANNs is the backpropagation of errors. The backpropagation algorithm falls into the general category of gradient descent algorithms, which intend to find the minima/maxima of a function by iteratively moving in the direction of the negative of the slope of the function to be minimized/maximized. The main objective is to minimize the error function. In this algorithm, the weights and biases are updated on a pattern-by-pattern basis until one complete epoch has been dealt with. The adjustments to the weights are made in accordance with the respective errors computed for each pattern presented to the network. The arithmetic average of these individual weights over the entire training set is an estimate of the true change that would result from the modification of the weights based on the error function. A gradient descent strategy is adopted to minimize the error.

Thus, ANNs have a built-in capability to adapt the network parameters to the changes in the studied system. A neural network trained to a particular input data set corresponding to a particular environment; can be easily retrained to a new environment to predict at the same level of environment. However, while blessed with good predictive performance, ANN is a black box algorithm, and hence does not provide any information regarding the relative importance of predictor variables used in the model.

2.2 Random Forest

Random Forest is an ensemble method, whereby a combination of Classification and Regression Trees (CARTs) are used; with the individual outputs from each of the CARTs finally combined to generate the output for the Random Forest. The results are combined by a method of voting for classification, and by a method of averaging the individual outputs in case of regression to arrive at the final result, the latter being the one used in our models.

Each of the CARTs in Random Forest are grown randomly from the training dataset provided to train the Forest. The individual trees are grown using different training sets. A random vector Θ_k is generated to grow a tree from the training set provided to train the Random Forest. Θ_k is independent of past random vectors Θ_1, Θ_2, …, Θ_(k-1), but follow the same distribution. The training sets used to develop the various trees are derived by randomly drawing the records, with replacement, using the random vector Θ_k, from the training set originally provided for the Random Forest. A new tree is grown with each of these new training sets using random feature selection. These trees are allowed to grow without pruning. Each individual tree is thus a classifier or regressor of the form $\{h(x, \Theta_k), k = 1,2,..\}$.

It has been shown that for a large number of trees, because of the law of large numbers, Random Forest does not overfit, instead, it produces a limiting value of generalized error. Random Forest also does not provide much insight into the model building, it does compute and provide the relative importance of predictor variables in the model.

3. Literature Review

The increasing empirical evidences on the liquidity and stock market nexus in quite voluminous. Kumar and Misra (2015) provide an excellent review of the frameworks currently available for modelling liquidity. Here we attempt to review the most influential studies in this area. Chordia et al. (2001), use trading activity and turnover rate to conclude that liquidity has a negative effect on risk-adjusted stock returns, which was supported by Pastor and Stambaugh (2003); Marshall and Young (2003) and Moore and Sadka (2006) for different markets. On the Spanish stock market, Martinez et al. (2005) observe a significant and positive relationship between the Amihud (2002) illiquidity measure and returns in both the unconditional and conditional asset pricing models. Moreover, using the Pastor and Stambaugh (2003) liquidity measure, they find a significant negative relationship in only the conditional asset pricing model. However, when they use the bid-ask spread as a proxy for liquidity, they do not find any relationship. Faff et al. (2010) report a negative association between expected stock returns and liquidity measures but contrary to perceived notion that liquidity is more important during bear phases, they observe that liquidity is priced during expansionary phase of business cycle but not significantly priced during contraction phase. This apparent consensus of a negative relation between stock-level liquidity and expected returns, a persistent negative shock to a security’s liquidity should, as pointed out by Acharya and Pedersen (2005), result in low contemporaneous returns and high future returns, and vice versa, has been challenged on numerous occasions. It is argued that this prediction of a negative relation between liquidity shocks and future returns may not hold in a market in which information is not fully reflected into prices due to market frictions. Bali et al. (2014) provide evidence that stock markets underreact to stock-level liquidity shocks and liquidity shocks are not only positively associated with contemporaneous returns, but they also predict future return continuations for up to six months. Batten and Vo (2014) observe a positive relation between liquidity and stock returns for emerging equity markets which contradicts the negative correlation typically found in stock returns in developed markets obtained earlier. Most of the work on liquidity has used standard econometric techniques. However, machine learning algorithms were used by some authors for stock market prediction. While Dutta et al. (2006) evidence that ANN performs satisfactorily in predicting closing prices of SENSEX, the leading index of Bombay Stock Exchange, Qin et al. (2012) evidence support for Random Forest based trading model for the Singapore exchange. Sala (2011) develops an alternative approach of liquidity risk modelling using a recurrent neural network and shows that machine learning may be an important alternative while modelling liquidity risk. In the Indian context, Krishnan and Mishra (2013) explore liquidity patterns in the Indian stock market while Kumar and Mishra (2015) explore patterns for individual stocks, we did not find any study in Indian context that uses liquidity measures to explain stock market movements.

Clearly evidences on effects of liquidity on stock market do not seem to converge but still there is a general consensus that liquidity reduces returns, and often empirical evidence supports the idea that risks emanating from liquidity need to be priced. It follows that an investigation on whether or not liquidity risk needs to be priced on the Indian stock market offers a fresh perspective on the liquidity-return nexus and worth a review. Given the idiosyncrasies of Indian equity market, the study attempts to explore whether stock market return variations can be explained by collection of liquidity measures used in the literature and if the two major Indian stock exchanges NSE and BSE differs in terms of liquidity. Also there is a natural need to vouch and verify the existing research findings especially with emergence of changing microstructure.

4. Data

In this paper, to gauge the robustness of the effect of liquidity on returns, we consider five liquidity measures. Following Korajczyk and Sadka (2008), we use trading volume and the turnover rate as measures of liquidity. Amihud and Mendelson (1986) suggested the strong theoretical background for the use of the turnover rate arguing that liquidity is correlated with trading frequency in equilibrium, and is well discussed in Datar et al. (1998). The turnover considered here is the ratio of monthly trading volume and market capitalization. In addition, we follow Narayan and Zheng (2011) and consider the trading probability as an additional measure of liquidity, which is calculated as:

$$\textit{Trading Probability (Tp)} = 1/\,(1 + \textit{the number of non-trading days in a month}) \qquad (2)$$

They used this measure to capture the speed dimension of liquidity and avoid the bias effects from the noise in the market as a noisy market have more risks of serial correlation effects.

We also consider the spread (high minus low) that captures the transaction costs and market efficiency coefficient (MEC) for resiliency. MEC measures the impact of execution costs on price volatility over short horizons and compares the long-term variance with the short-term variance. The variance of transaction prices are expected to be smaller in a liquid market. MEC is calculated as:

$$\text{MEC} = \frac{\text{Long Term Variance}}{\text{T} \times \text{Short Term Variance}} \qquad (3)$$

where T is the number of sub periods into which longer periods of time can be divided. We considered 5 days as short period and 30 days as long period i.e., T = 6. When MEC is less than 1 but close to it, it suggests that the market is resilient and minimum price volatility is expected.

The study focuses on two major stock exchanges of India – National stock Exchange (NSE) and Bombay stock Exchange (BSE) and considers two composite indices NIFTY 500 and BSE 500. The indices values are taken into their natural logarithm form (lnindex). The idea is to consider a well-diversified index from each exchange and so that it consists of companies of different market capitalization and categories (types).

5. Methodology

The time period considered is July 2002 to February 2016. Time series data are obtained from Bloomberg and liquidity variables are calculated. We first study the descriptive statistics of all the variables considered including their time series characteristics. Then we used machine learning techniques - Artificial Neural Network and Random Forest - to explore as to whether stock market is related to the liquidity measures considered. ANN and RF are arguably the most frequently used machine learning algorithm, and can learn any linear or non-linear function. Given the dynamic nature of the system under study, machine learning suits better than other traditional models in predicting the stock market as it can change its network parameters (synaptic weights and node biases) in real time. A feed forward neural network with standard backpropagation leaning function was used to learn the following:

$$\text{lnIndex} = f(\text{tp}, \text{lnsp}, \text{mec}, \text{lntv}, \text{Turnover Rate}) \quad (4)$$

Also, since RF has been found to have good predictive power in case of non-linear data and can learn the relationship from the data without any a priori knowledge of such relationships as in case of ANN, RF was used to learn the relationship in the above equation. In case of the machine learning algorithms of ANN and RF, the available monthly records for NSE and for BSE were partitioned into two partitions each – one for training the ANN and RF models, and the other for evaluating the performance of the trained model using the remaining data. The training partition was built by randomly picking up 70% of the records, without replacement, from the available data. All the input and output variables are contemporaneous aiming to explore a possible relationship between the liquidity dimensions and stock market movements. The training partition for NSE data contained the records of the same data as those in the training partition for BSE data. The same was the case with the partitions created for validating the models for BSE and NSE data, respectively.

Further, we tested whether liquidity in BSE and NSE are different in terms of the parameters used in this study. Hence, we tried non-parametric tests under the null hypothesis that two independent samples are from populations with the same distribution by using the Wilcoxon rank-sum test and the Kolmogorov-Smirnov test for equality of distribution functions to explore whether there is some level of equality in terms of liquidity parameters.

6. Findings & Analysis

6.1 Descriptive Statistics

Table 1: Descriptive Statistics of the variables (NIFTY 500)

	lnindex	Lnsp	Lntv	Mec	Tp	Turnover Rate
Mean	8.05	5.60	22.66	0.57	0.09	0.45
Median	8.28	5.73	22.97	0.35	0.09	0.42
Maximum	8.89	7.51	23.87	3.42	0.12	1.06
Minimum	6.54	3.36	20.59	0.09	0.07	0.21
Std. Dev.	0.62	0.72	0.79	0.53	0.01	0.13
Skewness	-0.94	-0.58	-0.94	2.21	0.14	1.28
Kurtosis	3.02	3.36	2.89	8.96	2.53	4.95
Jarque-Bera	23.91***	10.38***	24.52***	375.91***	2.08	71.02***

Note: The Table 1 above shows the mean, median, range, standard deviation and the third and fourth moments of the independent and dependent variables related to NIFTY 500. Except for trading probability, the Jarque-Bera statistics are significant for all series at 1% level (denoted by ***) indicating rejection of null hypotheses of normal distribution for these series.

Table 2: Descriptive Statistics of the variables (BSE 500)

	Lnindex	Lnsp	Intv	Mec	Tp	Turnover Rate
Mean	8.50	6.07	27.22	0.66	0.09	0.31
Median	8.75	6.21	26.98	0.45	0.09	0.21
Maximum	9.35	7.96	29.42	5.39	0.13	1.11
Minimum	6.96	3.81	25.74	0.09	0.07	0.04
Std. Dev.	0.63	0.73	0.80	0.69	0.01	0.03
Skewness	-0.94	-0.61	0.67	3.67	0.10	0.88
Kurtosis	2.99	3.35	2.82	21.43	2.36	2.56
Jarque-Bera	24.51	11.27	12.49	2691.61	3.12	22.74
Probability	0.00	0.00	0.00	0	0.21	0.00

Note: The Table 2 above shows the mean, median, range, standard deviation and the third and fourth moments of the independent and dependent variables related to BSE 500. Except for trading probability, the Jarque-Bera statistics are significant for all series at 1% level (denoted by ***) indicating rejection of null hypotheses of normal distribution for these series.

6.2 Measures of Liquidity (Trend Analysis)

Sarr and Lybek (2002) are in favour of using market indices as a proxy for stock market with the caveat that they cover only the important stocks. Figure 2 and 3 below shows general liquidity measures of Indian equity markets using BSE500 and NSE500 indices.

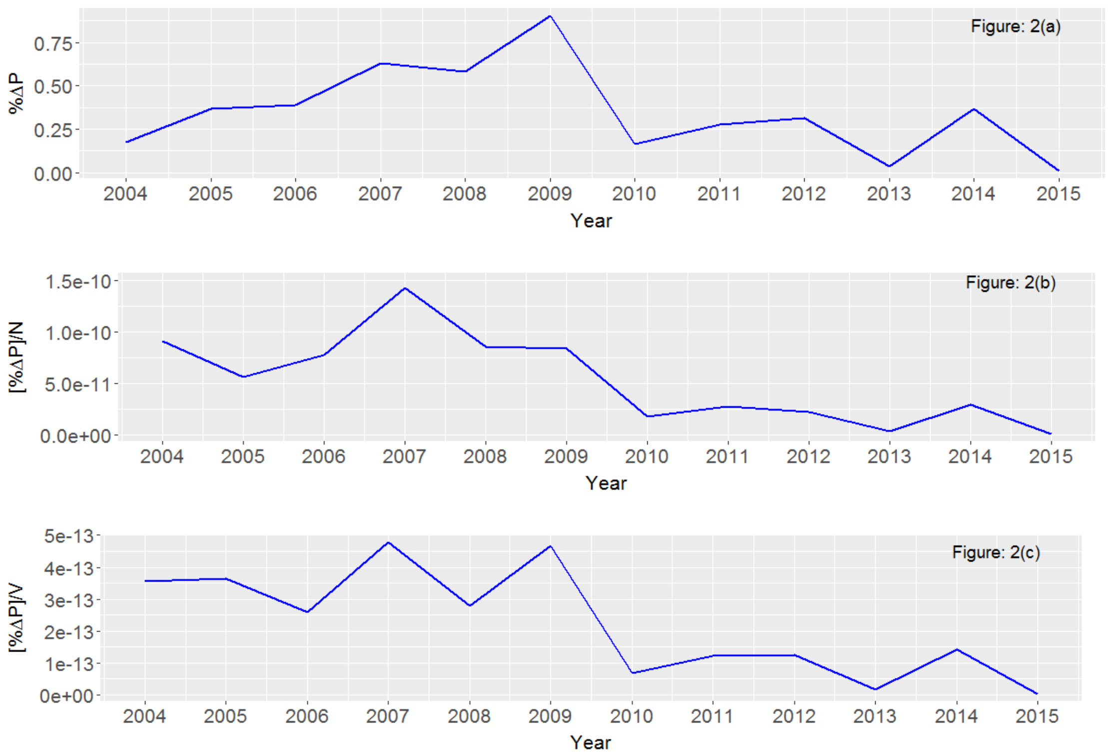

Figure 2: General Liquidity Measures – BSE 500

It is seen that in case of BSE 500 data, the volatility of the index as measured by the percent change (figure 2(a)) has increased from 2004 only to shoot up during 2007 to 2009, where equity markets around the globe were affected due to series of economic news and events post US led financial crises. The market remained flat for the majority of the time after 2010 and showed signs of volatility when India had its general election which brought a stable government in power. From 2015 onwards the market remained flat due to lack of positive global news with domestic good news being possibly nullified by negative sentiments about the Chinese economy.

The conventional liquidity ratio (figure 2(b)) relating to price changes to number of units traded have shown a upward trend since 2005, reaching its peak during 2007 and then came down till 2010 from where it fell to its lowest in 2013 and 2015.

Another conventional liquidity ratio (figure 2(c)) relating to value of transactions had its peak during 2007 only to fall in 2008, climb up again in 2009 and then sharply came down in 2010 from where it fell to its lowest in 2013 and 2015. Thus the conventional liquidity measures showed a similar type of trend from 2004 to 2007, when volatility of the index was increasing. This consistency in the behavior of conventional liquidity measures in the face of increased (decreased) price volatility can be interpreted as increase (decrease) in market depth.

After 2009, when fluctuations in the volatility of the index was observed, the conventional liquidity ratios also increased. This might be because of the reason that number of units traded (N) and turnover (V) have not experienced the same increase as before. So the possibility of a reduction in market depth cannot be ruled out post 2009.

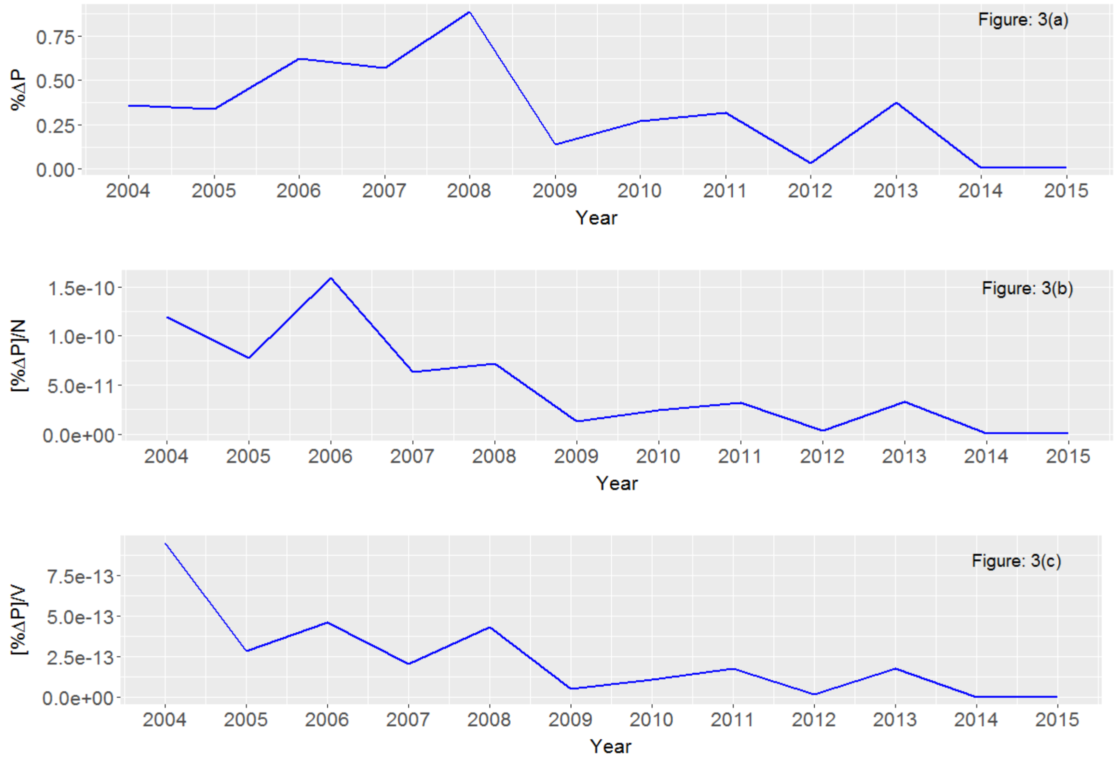

Figure 3: General Liquidity Measures – NSE 500

It is seen that in case of NSE 500 data, the volatility of the index as measured by the percent change (figure 3(a)) increased from 2004 to 2007-08, but a sharp fall was observed in 2008-09, thereafter it followed the same behavior as shown in BSE 500 series volatility.

The conventional liquidity ratio (figure 3(b)) relating to price changes to number of units traded have shown a downward trend since 2006, with sharp fall in 2007 and 2009 and was significantly low during 2014 and 2015.

Another conventional liquidity ratio (figure 3(c)) relating to the value of transactions has shown a downward trend since 2004 with sharp fall in 2007-08, and remained flat during 2014-15.

Thus the conventional liquidity measures showed a similar type of trend from 2004 to 2006, when the volatility of the index was increasing. This consistency in the behaviour of conventional liquidity measures in the face of increased price volatility can be interpreted as an increase in market depth. After 2007, when fluctuations in the volatility of the index was observed with cyclical ups and downs, the conventional liquidity ratios also started increasing. The number of shares traded (N) and turnover (V) have not experienced the same increase as before and thus the indication of a reduction in market depth during post financial crises period.

However these observations needs to be supplemented with other liquidity measures as discussed under methodology section and is reported below.

6.3 Market Efficiency Coefficient (MEC)

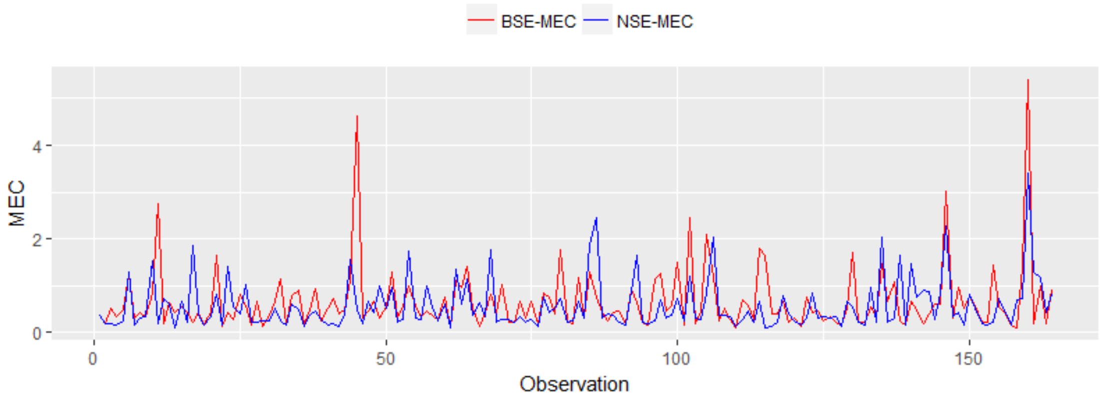

Figure 4: Market Efficiency Coefficient

The MEC exploits the fact that price movements are more continuous in liquid markets, even if new information is affecting equilibrium prices. The ratio should be closer but slightly below one in a more resilient market. MECs (BSE) are mostly around one fluctuating above and below it during the time period of the study with some outliers. So we can infer that the market was mostly resilient and a short term volatility is an expected fact when MEC is substantially below one.

MEC (NSE) was closer to one, fluctuating both above and below it with few outliers. A MEC greater than one may not be surprising as market maker intervention, inaccurate price determination involving partial adjustment to news causes prices to adjust in relatively small and positively correlated increments and this would dampen short price volatility to longer period volatility and may cause the MEC to be above one.

6.4 Turnover Rate or Turnover Velocity

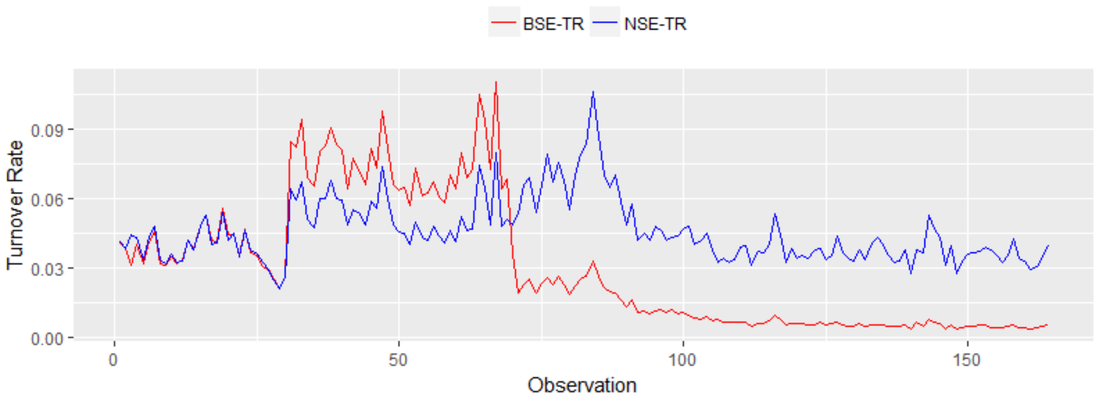

Figure 5: Turnover Rate

The Turnover rate or turnover velocity shows slightly different behaviour for BSE and NSE. At BSE, the rate was on higher side during mid-2004 till 2007 and then decreased sharply during 2008, possibly an effect of global financial crises. Since then it had a downward trend and remained low with lower fluctuations suggesting evidence of reduced breadth. In case of NSE, it picked up from mid-2004, was on the higher side till 2007and came down in 2007 and then again picked up from 2008 only to come down at around pre 2004 level and stabilized there. But it's important to note that this stabilized rate is much higher in NSE than in BBE.

6.5 Spread

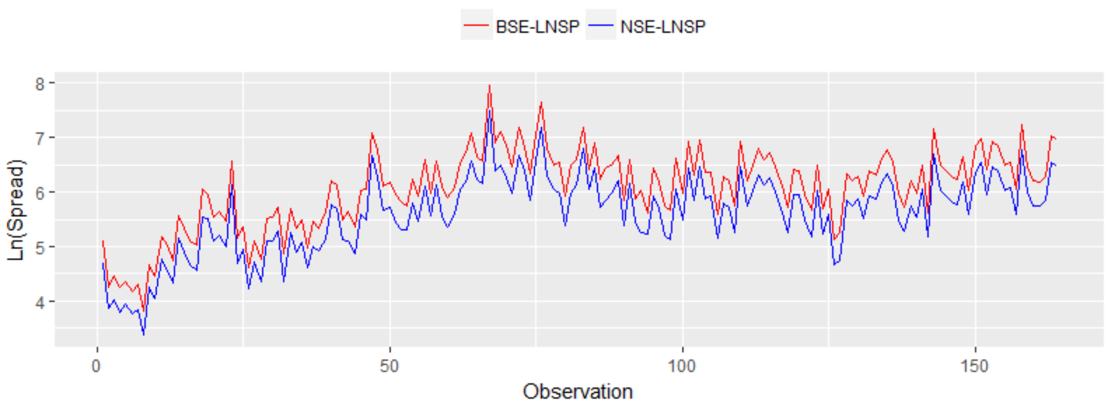

Figure 6: Spread

Trend Analysis of spread gives almost similar outcome for both the indices with spread at high levels during 2007-08 then gradually coming down with fluctuations. High spread during crises and/or world recession period led to reduced liquidity as indicated by high spread. However both BSE and NSE shows upward trends at decreasing rate.

6.6 Trading Volume

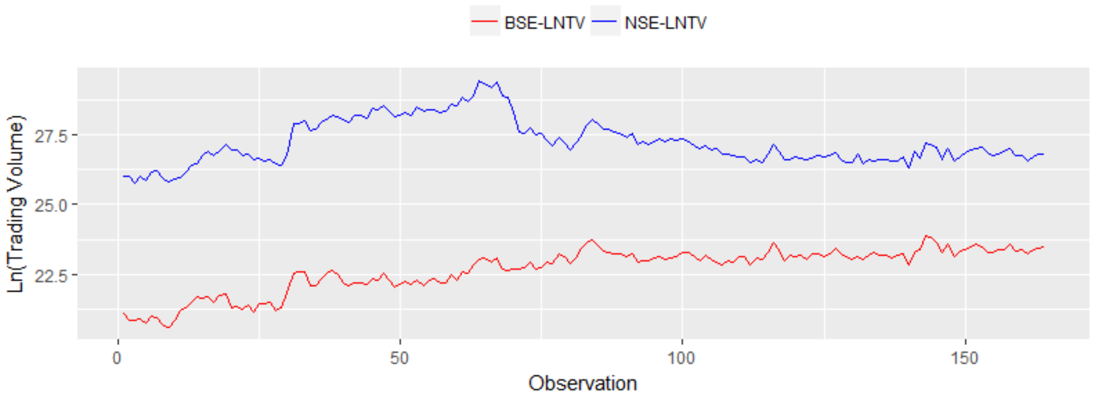

Figure 7: Trading Volume

Trading volume is a traditional measure of liquidity as Market liquidity refers to the extent to which a market allows assets to be bought and sold at stable prices. The trend analysis of trading volume of BSE and NSE gives clear indications that BSE is steadily decreasing its trading volume and liquidity while NSE's trading volume and liquidity is growing. There were obvious ups and down during global events like during financial crises, both the markets crashed but NSE picked up subsequently while the BSE could not. Even a fall in indices due to the Chinese equity meltdown and rupee crashing against the dollar in 2015 led to a spurt in trading volume as panicked investors hit the exit button.

6.7 Trading Probability

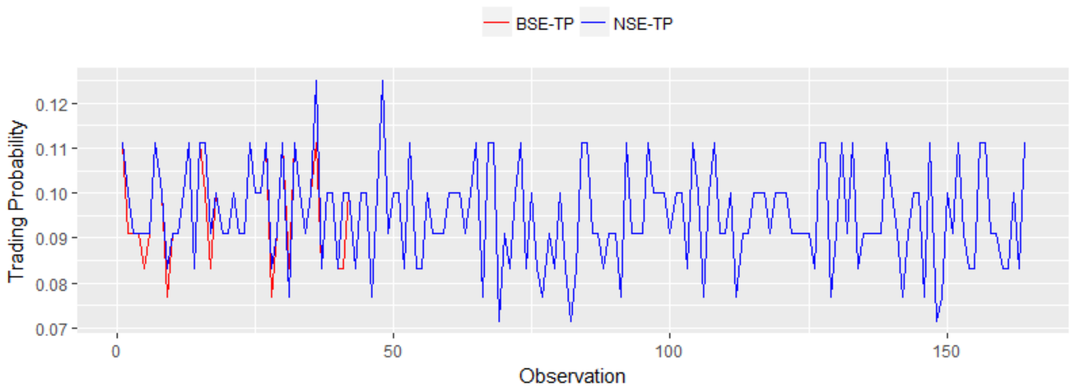

Figure 8: Trading Probability

The Trading Probability measure seems to function as an alternative to the usual logarithm of Size variable. It is expected to capture one of the dimensions of liquidity viz., Trading Speed. We observe that trading probability trend in BSE and NSE are almost similar during study period.

6.8 Artificial Neural Network (ANN)

The network used was a simple one which had one hidden layer with three nodes (H1, H2, and H3), and is represented below (Figure 9):

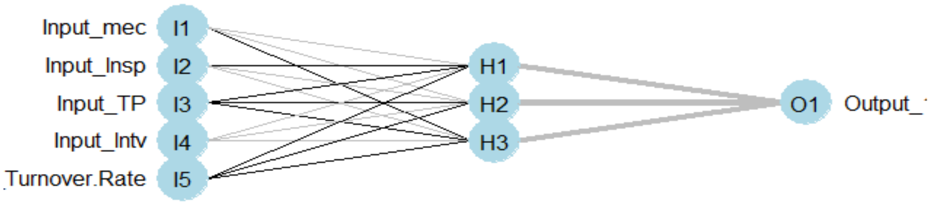

Figure 9: ANN used in the study having one hidden layer and three nodes

The five nodes (I1, I2, I3, I4, and I5) in the input layer took in the five inputs to the model – trading probability (tp), spread (lnsp), Market Efficiency coefficient (mec), trading volume (lntv), Turnover rate, and the output node (O1) provided the computed value of lnIndex. H1, H2, and H3 were the three hidden nodes in the single hidden layer used in the model.

The neural network models were developed in R using the RSNNS library [1], using logistic activation function at the hidden as well as output layers. The performance of the models was evaluated using the Mean Average Percentage Error (MAPE) computed based on the dependent variable computed by the trained model using the data from the respective validation partitions.

As ANN works best with inputs and outputs in the range 0 to 1, we scale the data to that interval while using ANN models. The corresponding output, while using the model for predicting the lnindex was converted back to the original scale for comparison with the observed values and computing the MAPE.

Error measurement statistics play a critical role in tracking forecast accuracy, monitoring for exceptions, and benchmarking your forecasting process. On modeling the liquidity variables using ANN we obtained MAPE of 5.65% for BSE and 5.81% for NSE. MAPE is the relative significance (Percentage) of the error and a value of about 5% using ANN can be considered pretty useful as far as ANN related studies are concerned. Empirical evidences using Normal Regression generally show higher MAPE values.

We had also tried with more complex MLP ANNs, with one to three hidden layers with three to fifteen nodes in each hidden layer, but the best MAPE were obtained for the aforesaid simple network of one hidden layer with three nodes in it. This indicates the presence of a comparatively simpler relationship between the predictor variables and the predicted one.

6.9 Random Forest (RF)

The Random Forest model was built using the Random Forest library of R. The RF was built with 500 trees, and in addition to MAPE for the predicted values of lnindex, relative importance of the different predictor variables was also computed.

As mentioned earlier, while Random Forest is a black box algorithm with a good predictive performance, it does allow certain visibility about the importance of predictor variables used in building the model. One of the important measures that

Random Forest uses to decide on the importance of a given predictor variable is through computation of the increase in MSE of prediction if the given predictor variable has its value permuted, that is, if the values of that predictor variable are replaced with other realistic values. Thus, for a large value of MSEj, the increase in MSE of prediction by permuting the values of predictor j, implies that the predictor j was important in building the model. The MAPE obtained using RF for BSE is 2.17% and for NSE is 2.41%. They are even better than those obtained from ANN models. Both the findings from machine learning tools individually as well as collectively support the existence of a good relationship between the predictor variables (liquidity measures) and the predicted ones (stock market). Figure 10 shows the relative importance of the predictor variables used in the model:

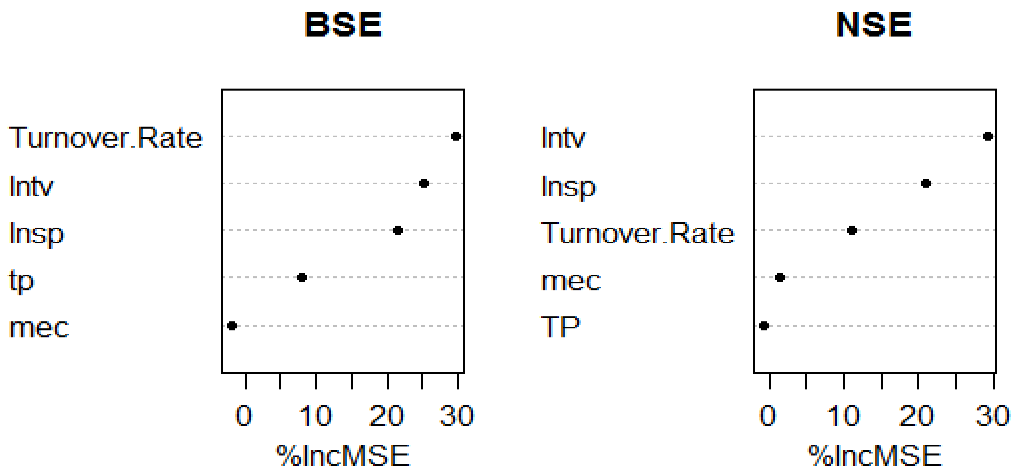

Figure 10: Relative importance of liquidity measures in BSE and NSE

The plot of the predictor variables vis-à-vis the percentage increase in MSE (%IncMSE), the predictor with the highest increase in MSE being the most important player in the model, indicates that the most important predictor variables are Intv (trading volume), Insp (Spread) and Turnover Rate. The findings are consistent for both the exchanges and hence may be generalized for Indian stock market.

6.10 Wilcoxon rank-sum and Kolmogorov-Smirnov tests

The findings are tabulated below in Table 3. It shows the status of null hypothesis of equality (using 5% level of significance) under respective tests for each liquidity measure. Under Wilcoxon rank-sum test, we additionally give an estimate of the probability that a random draw from the first population (i.e., NSE) is larger than a random draw from the second population (i.e., BSE)

We find that liquidity measures in terms of volume, spread, turnover rate and MEC are significantly different in NSE and BSE as per the non-parametric tests used above. The probability estimates that a liquidity parameter of NSE is higher than BSE is more than 50% in all cases except Spread suggesting that there are more chances that BSE might be less liquid than NSE and this finding is consistent with other findings here. Spread is an indicator of tightness and a narrow spread indicates a liquid market. Null hypothesis of equality could not be rejected for trading probability and this may not be surprising as TP is a function of no. of trading (or no of non-trading days) and generally both the exchanges observes holidays on same day in India.

Table 3: Test of Equality between NSE and BSE

	Volume	TR	Spread	MEC	TP
Wilcoxon rank-sum test	Rejected. P{volume(NSE) > volume(BSE)} = 0.725	Rejected. P{TR(NSE) > TR(BSE)} = 0.717	Rejected. P{spread(NSE) > spread(BSE)} = 0.313	Rejected. P{MEC(NSE) > MEC(BSE)} = 0.557	Accepted. P{TP(NSE) > TP(BSE)} = 0.549
Kolmogorov -Smirnov test	Rejected.	Rejected.	Rejected.	Rejected.	Accepted.

7. Conclusion

The paper explores the liquidity position of two broad based stock index from Indian Stock Market in terms of market depth, breadth, and resiliency and attempts to investigate whether the endogenous liquidity measures collectively are capable of explaining changes in those chosen indices. We observe through the time period 2002 to 2015 and under all chosen measures that liquidity was affected during the period of global financial crisis and its recovery period. In fact all measures showed India is still lacking both market depth and breadth when compared to pre-crisis period. The MEC values clearly indicate that resiliency in Indian stock market keeps changing with observed volatility coming down in recent years. The conventional econometric models using time series data show lower levels of accuracy and parameter instability in modeling liquidity and stock market possibly due to non-linearity in the data series. Alternatively, Artificial Neural Networks (ANN) and Random Forest (RF), due to its unique non-parametric, non-assumable, noise-tolerant and adaptive properties, can map any nonlinear function without a priori assumptions and has shown great applicability in time-series analysis and forecasting due to its pattern recognition capability. Using five proxies as a liquidity measures: namely trading probability, spread, Market Efficiency coefficient, trading volume and turnover rate and ANN we obtained a MAPE (mean absolute percentage error) of 5.65% in case of BSE 500 series and a MAPE (mean absolute percentage error) of 5.81% in case of NIFTY 500 series while using RF the errors were lower further. Also RF showed that traded volume, spread and turnover rate (or turnover velocity) are most important liquidity variables for explaining variations in stock market indices. The non-parametric tests indicates that chances are higher that liquidity of the BSE is lower compared to the NSE. This supports the BSE's latest decision to offer 'Liquidity Enhancement Incentive Programmes Schemes (LEIPS)' to as many as 166 securities exclusively listed on the stock exchange and create a new sub-group named 'XC' group for companies listed exclusively on it. Overall, the study provides more support to liquidity measures as an important factor for explaining variations in stock market especially in the Indian context.

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MOVING AVERAGE TRADING RULES FOR NASDAQ COMPOSITE INDEX

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Abstract: This paper tests a few moving average technical trading rules for the NASDAQ Composite index from 1972 to 2015. Our results indicate that moving average (MA) rules do exhibit strong predictive power for NADSAQ composite index. Can a trader use this predictive to beat the Buy and hold strategy? We show that MA-100 days can, most of the time, make an abnormal profit in the case of NASDAQ composite index by considering both transaction costs and risk. In addition RSI and MACD trading rules have also strong predictive power.

Keywords: moving average, trading rules, abnormal profit, market efficiency, transaction costs

1. Introduction

The Efficient Market Hypothesis (EMH) has provided the foundation of many academic textbooks in finance and investments. The EMH suggests that investors cannot expect to outperform the market consistently. This is because securities prices fully reflect all available information; any new information will be quickly and instantaneously reflected in prices (Fama, 1970). Since securities prices incorporate all known information and new information comes randomly, day-to-day price changes follow a random walk over time, although with a positive drift. A random walk implies any price pattern is accidental and if securities prices follow a random walk, trading rules and other Technical Analysis (TA) methods of predicting securities prices will be useless.

Contrary to the above suggestion, there are many traders using TA principles to predict future prices. TA can be dated back hundreds of years ago. According to historical records, a great Japanese rice trader by the name of Homma Munehisa (1724-1803) who fathered candlestick charting at today's value, would have made over $100 billion in profits and been considered as the greatest trader in history of financial markets. In the U.S., technical analysis was initiated by Charles Dow (1851-1902), the founder of Wall Street Journal and Dow Chemical. Today many traders still follow his Dow Theory for buy and sell signals and the Dow Jones Industrial Index still serves as one of the most important reflections for the U.S. stock market.

The development of technical analysis is based upon three assumptions: 1) the market discounts everything. In other words, all of financial positions of a company are reflected in its stock price; 2) price moves in trends; that is, a trend line will be of tremendous help to predict the future prices. Early detection of a trend is essential to the success of TA. One of the most important trend determining techniques is the use of moving average (MA) employed in this paper; and 3) history tends to repeat itself; this implies traders and investors will react in same way to the same conditions which will create opportunity for profitable trading. As Meyers (2002) states: “Technicians record, usually in chart form, historical price and volume activity and deduce from that pictured history the probable future trend of prices.”

The purpose of this paper is twofold. First, we examine whether moving average (MA) trading rules have predictive power in the NASDAQ composite Index (NASDAQ); and secondly, if MA trading rules do exhibit predictive power, could a trader design a strategy to beat the profitability of the buy and hold (B&H) strategy, considering transaction costs and risk? Our results indicate that MA trading rules do exhibit strong predictive power for NADSAQ composite index. A trader employing MA-100 trading rule could most of the time make an abnormal profit even considering both transaction costs and risk. We also develop two strategies associated with MA-100 for different risk-tolerance traders to beat handsomely the buy-and-hold NASDAQ strategy. In addition we show that the RSI and MACD trading rules have also strong predictive power.

The remainder of this article is organized as the following. Section 2 details some of the relevant literature. Section 3 describes the data and methodology. The empirical results of various moving average trading rules are exhibited in Section 4. Section 5 compares different strategies to locate the most profitable strategies to beat the buy-and-hold strategy considering transaction costs and market risk. The final section provides concluding remarks.

2. Literature Review

It is possible to trace the history of TA back to 17th century, an Amsterdam trader, poet, and philosopher, Joseph Penso de la Vega. However as we have mentioned above, the fathers of modern TA are the Japanese rice trader, Homma Munehisa (candlestick charting) and Charles Dow the founder of Wall Street Journal and Dow Theory. In the 1920s and 1930s, Richard W. Schabacker published several books which continued the work of Charles Dow and William Peter Hamilton in their books Stock Market Theory and Practice and Technical Market Analysis. In 1948 Robert D. Edwards and John Magee published Technical Analysis of Stock Trends, which is widely considered, even today, to be one of the seminal works of the TA. Other pioneers contributed to TA including Ralph Elliot (the Elliot wave principles) and William Gann (the Gann angles and arcs). Most technicians were Wall Street traders and most finance professors were believer of EMH. In early 1970s and 1980s, the Random Walk Hypothesis and its close relative EMH had become icons of modern financial economics that continue to have many followers in academic circles as well as professional fund manager in today’s world. As Lo and MacKinley (1990) point out, even after three decades of research and thousands of journal articles, finance professors and economists have not yet reached a conclusion about whether financial markets are efficient or not. Early well-known empirical studies supported weak form market efficiency, implying that a trader cannot use past prices to forecast future prices. See for example Larson (1960), Cowles (1960), Granger and Morgenstern (1963), Mandelbrot (1963), Alexander (1964), Fama (1965), Fama and Blume (1966), Van Horn and Parker (1967), and Jensen and Benington (1970).

However since the mid-1980s, technical trading has enjoyed a renaissance both on Wall Street and in academic circles. Several papers have questioned the validity of EMH by demonstrating that simple technical trading strategies possess significant power to predict future security prices. The cornerstones of this renaissance in technical analysis were articles by Sweeney (1986), Lukac et al. (1988), and Brock, Lakonishok and LeBaron (1992, BLL hereafter). Sweeney (1986) applies some filter rules for ten currencies and find that various filters were profitable in more than 80 percent of the cases. Lukac et al. (1988) find that moving average rules statistically beat the buy and hold strategy. In 1992 a seminal paper by BBL analyzes moving averages and trading rules on the Dow Jones Industrial Index for a period of 89 years from 1897 to 1985. They use various short and long moving averages of prices to generate buy and sell signals. They point out that 'all buy-sell differences are positive and the t-tests for these differences are highly significant…' and they go on to conclude that their 'results are consistent with technical rules having predictive power'.

Park and Irwin (2007) provide an excellent survey of technical trading rules by differentiating the early studies from the modern studies; they conclude that early studies do not support the predictive power of TA for equity market, and 56 out of a total 95 modern studies support profitable trading rules. The bulk of modern studies suggest that trading rules, especially the moving average rules, exhibit predictive power. However, whether applying those trading rules to obtain abnormal profits when including transaction costs and risk is not clear for most indexes

3. Data and Methodology

In this paper, we employ a simple technical analysis approach to test the predictive power for Nasdaq Composite index. The exchange traded fund (ETF) that mimics NASDAQ composite index has been listed on the NASDAQ National Market and has been traded since October 1, 2003 (ticker symbol: oneq).

We use Datastream's daily closing price of the NASDAQ composite index over the period of 1/3/1972 to 10/14/2015 and define the daily returns as changes in logarithms of the each index price. Although estimating the return this way does not consider dividend yield, Mills and Coutts (1995) review the literatures regarding dividends exclusion and conclude that any bias in the results due to dividend exclusion will be minimal. This conclusion is also supported by Draper and Paudyal (1997). The proxy interest data (i.e. money market rate) used in this study is from Datastream's daily Federal Fund rate. In order to get the daily interest return, we follow Lucke (2002) by dividing the annual rates by 260.

The art of technical analysis – in fact it is an art to identify trend changes at an early stage and to maintain an investment position until the weight of evidence indicates that the trend has been changed (Pring, 1991). As Kirkpatrick and Dahlquist (2015) point out, one of the most successful techniques of identifying and profiting trends is the use of moving averages. According to MA rules, buy (sell) signals are generated when a short-term moving average exceeds (is less than) the long-term moving average by a specified percentage. In this study we use the long-term moving averages of 20, 50, 100, 150 and 200 days. As for the short-term moving average, like the BLL study, we use 1 day (the raw price) moving average. Thus, a buy signal is emitted when the index price level breaks the long MA from below and a sell signal is emitted when the index level breaks the long MA from above.

We define Pt as the short-term moving average or the raw index level at time t, and define the long-term moving average of M-day at time t as:

$$MA_t(M) = \frac{1}{M}\sum_{i=0}^{M-1} P_{t-i}\,. \qquad (1)$$

An investor/trader who follows MA trading rules could presumably estimate the index price that would trigger the buy and sell signal just before the day's close and initiate a conditional limit order at the close of the market to perform various trading rules. For example a trader that has been out of the market following a trading rule based on MA50 (if P > MA50, in the market and if P ≤ MA50 then out of the market) could have the following conditional limit order at the close of the day: If the price index is above previous close of MA50, then buy market on close (MOC). Therefore the trader will be in the market the next day by buying the index at the closing limit price (i.e. next day will be a buy day). The next day's return will be the change in logarithms of the index level. The same reasoning holds if the trader has been in the market, sell the index MOC if price is below previous close of MA50 (i.e. next day will be a sell day). The next day's return will be the change in logarithms of the index level. If the conditional limit prices are not filled, then the trader will not switch position. The trader is either in the market "buy" days or out of the market "sell" days, again the sell days mean the trader is out of the market and not shorting the market.

We define mean buy and mean sell day returns as follows:

$$\mu_b = \frac{1}{n_b}\sum R_b \qquad (2)$$

$$\mu_s = \frac{1}{n_s}\sum R_s \qquad (3)$$

where, R_b and R_s are daily returns of buy and sell days; n_b and n_s are the total number of buy and sell days respectively. We will test whether the returns of any moving average trading rules are greater than a B&H strategy and whether the mean buy is different from the mean sell. The null and alternative hypotheses are expressed in Table 1:

Table 1: Test Hypotheses

	Test One	Test Two	Test Three
Null: H_0	$\mu_b - \mu_h = 0$	$\mu_s - \mu_h = 0$	$\mu_b - \mu_s = 0$
Alternative: H_a	$\mu_b - \mu_h \neq 0$	$\mu_s - \mu_h \neq 0$	$\mu_b - \mu_s \neq 0$

where μ_h is the mean of the B&H strategy. Following Kwon and Kish (2002), the test statistic for the Test is:

$$t = \frac{\mu_b - \mu_s}{\sqrt{(\sigma_b^2 / n_b) - (\sigma_s^2 / n_s)}}\,, \qquad (4)$$

where μ represents the mean returns, σ^2 is the estimated variance, and n is the number of observations in each situation. Statistically significant differences in buy-sell day index returns implies the effectiveness of the MA rules to forecast equity returns, this is the same procedure used by BBL. The above formula is also used for Test One and Test Two by replacing the appropriate variables in the t-statistic formula.

4. Empirical Results

In Table 2, we exhibit the summary statistics of daily returns for NASDAQ index in the entire 43.875 years with four sub-periods for comparison. For the entire period (01/72~10/15), the average daily return is 0.033% with a standard deviation of 1.23 over 11423 observations or days. The t-statistics for the mean returns of B&H in NASDAQ is 2.84. At the 5 percent confidence level for large numbers of observations, compared with the critical t-value 1.96 for two-tailed test, the unconditional means of NASDAQ for the entire period are significantly different from zero. The skewness implies that return distributions are almost symmetric for NASDAQ index. The Kurtosis is higher than 3, implying that the return distributions may not be normal, and the Jarque-Bera test rejects normality of returns in the entire period and all four sub-periods. All of the first and second order autocorrelations are low except for the first and second sub-periods.

Table 2: Summary Statistics of Returns: NASDAQ Composite Index

NASDAQ Composite Index								
Period	**Mean %**	**SD %**	**Skewness**	**Kurtosis**	$\rho 1$	$\rho 2$	*JB*	*n*
01/72 – 10/15	0.033%	1.23%	-0.29	10.08	0.05	-0.01	24046	11423
01/72 – 12/84	0.023%	0.76%	-0.77	3.91	0.32	0.08	453	3391
01/85 – 12/94	0.043%	0.86%	-2.28	30.79	0.26	0.05	86191	2609
01/95 – 12/04	0.041%	1.80%	0.01	4.05	0.00	-0.01	120	2610
01/05 – 10/15	0.028%	1.33%	-0.25	7.85	-0.07	-0.01	2788	2813

Note: SD = Standard Deviation; JB = Jacque Bra; critical value = 6; $\rho 1$ & $\rho 2$ = first and second order return correlations; n = total number of days in the period.

Table 3 summarizes the results of various moving average (MA) trading rules for the NASDAQ index. For each MA rule, we report mean buy returns, mean sell returns, the mean buy minus sell returns, standard deviations of returns on buy and sell days, total number of buy and sell days, and the number of signals generated. The numbers in the parentheses are the *t*-statistics defined in Equation *(4)* to test the difference of the mean buy and mean sell from the unconditional mean, and buy-sell from zero. For example, the first row of NASDAQ Composite Index shows the results of MA-20 trading rule. The trader will be in the market (buy days) if the index level is greater than MA20 and out of the market (sell days) if the index level is less than or equal to MA-20. Similarly, the other rows report the results of other MA-days trading rules.

Table 3: Statistical Results for Moving Average Rules

NASDAQ Composite Index								
Rules	Buy	Sell	Buy-Sell	*SDb*	*SDs*	n_b	n_s	No. of Signals
MA-20	0.00091 (3.60)*	-0.00054 (-3.46)*	0.00145 (5.76)*	0.00966	0.01539	6847	4576	1090
MA-50	0.00081 (3.01)*	-0.00047 (-2.98)*	0.00128 (4.82)*	0.00949	0.01583	7101	4322	605
MA-100	0.00068 (2.22)*	-0.00030 (-2.23)*	0.00098 (3.53)*	0.00929	0.01630	7300	4123	381
MA-150	0.00055 (1.45)	-0.00013 (-1.54)	0.00068 (2.33)*	0.00927	0.01681	7639	3784	347
MA-200	0.00054 (-0.20)	-0.00013 (0.23)	0.00067 (-0.31)	0.00948	0.01688	7835	3588	273

Moving average trading results for daily data from 1972-2015. n_b and n_s are the number of buy and sell days, SD_b and SD_s are standard deviation of buy and sell days respectively. The numbers in the parentheses are the t-statistics testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero. Numbers marked with asterisks are significant at the 5% level for a two-tailed test, $t_{crit., 0.05}$ =1.96.

The testing results of significance in Table 3 are very strong for NASDAQ. The mean buy and sell returns are shown in Columns 2 and 3. For MA20, MA50, and MA100 in NASDAQ, the mean buy returns are all positive with significant t-statistic and the mean sell returns are all negative with significant t-statistic. All the buy minus sell differences (Column 4) are positive and the t-test statistics are highly significant to reject the null hypothesis of equality with zero, except for MA-200. Therefore, the four out of five MA trading rules, MA20, MA50, MA100 and MA150 have predictive power in the NASDAQ Composite Index.

It is interesting to note that the standard deviations for buy days are always smaller than those for sell days in Columns 5 and 6. This implies that the down markets are more volatile than the up markets. Columns 7 and 8 report the number of buys and sells for various rules. For example when applying MA20 trading rule for NASDAQ, 60% of the days we are in the market (buy days) and 40% of the days out of the market (sell days). Finally the last column reports the number of signals for in and out of the market, as the MA days increases the number of in and out of the market decreases. It is also noteworthy to point out the negative returns for sell days is problematic for the proponents of EMH. As BLL indicates, these returns cannot be explained by seasonality since they are based approximately on 40% of all trading days. This predictability of returns can reflect either (1) changes in expected returns generated from an equilibrium model, or (2) market inefficiency. Although changes in expected returns are possible, it is hard to imagine an equilibrium model that predicts negative returns over such a large fraction of trading days.

The results in Table 3 indicate that moving average rules do indeed have predictive power for NASDAQ and can discern recurring-price patterns for profitable trading. Given the predictive power of MA rules, the next section discuss how can we design various trading strategies to beat the B&H strategy considering both transaction costs and market risk.

5. Trading Strategies

Now that we have confirmed the predictive power of MA rules for NASDAQ, we investigate whether it is possible to design various trading strategies for MA rules to beat the B&H strategy considering both transaction costs and risk. For each MA trading rule, the profitability will be varied with the position a trader takes when the rule emits sell signals. For example, if a trader does not invest in any alternative on the sell days (out of market), then his or her return on the sell days will be zero. Then the trader's mean return can be counted as simple as $(n_b/n)*\mu_b + (n_s/n)*0$. If a trader chooses to invest in the money market on the sell days, then the trader's mean return will include the interest earnings at money market rate on those sell days.

In this study, following Metghalchi et al. (2015), we consider a total of four strategies as the following:

Strategy 1 — The trader will be in the stock market when MA rules emit buy signals and be in the money market when a MA rules emit sell signals (long/money).

Strategy 2 — The trader will be in the stock market when MA rules emit buy signals and short the market when the rules emit sell signals (long/short).

Strategy 3 — The trader will borrow at the money market rate and double stock investment when trading rules emit buy signals and be in the money market when trading rules emit sell signals (leverage/money).

Strategy 4 — The trader will borrow at the money market rate and double stock investment when trading rules emit buy signals; short the market when the trading rules emit sell signals (leverage/short). Note that the total return on buy days for the leverage strategy is $TR_t = 2R_t - M_t$, where R_t is the index return on day t and M_t is the daily money market rate.

For each strategy, we estimate the daily return then subtract it from the daily return of B&H strategy to get the daily difference return. To test whether the average daily difference (*ddif*) is greater than zero or not, we express the null and alternative hypotheses as:

$$H_0: \ ddif \leq 0$$

$$H_a: \ ddif > 0$$

The t-statistic for the above test is:

$$t = \frac{\mu(ddif)}{\sqrt{\sigma^2(ddif)/n}}, \qquad (5)$$

where μ (*ddif*) is the average daily difference of returns of each strategy over the B&H strategy and σ^2(*ddif*) is the variance of daily difference returns, and n is the total number of days. Table 4 reports the results of the above six strategies for MA rules.

Table 4 shows the strong results with positive daily difference returns and significant *t*-statistics. At first glance, MA20 and MA50 rules with *Strategies 3, 4* are the most profitable rules and strategies. If market risk and transaction costs are not considered, then the best strategy would be to apply MA20 rule using *Strategy 4*, an extra return of 0.085% per day over the B&H strategy.

Table 4: Trading Strategies of MA Rules in NASDAQ

	Strategy 1	Strategy 2	Strategy 3	Strategy 4
	$\mu(ddif)$	$\mu(ddif)$	$\mu(ddif)$	$\mu(ddif)$
MA-20	0.00030 (3.33)*	0.00043 (2.36)*	0.00072 (6.31)*	0.00085 (4.27)*
MA-50	0.00026 (2.89)*	0.00035 (1.94)*	0.00064 (5.59)*	0.00073 (3.65)*
MA-100	0.00019 (2.09)*	0.00021 (1.16)	0.0005 (4.33)*	0.00052 (2.59)*
MA-150	0.00012 (1.35)	0.00009 (0.48)	0.00036 (3.13)*	0.00032 (1.60)
MA-200	0.00012 (1.35)	0.00009 (0.48)	0.00036 (3.13)*	0.00032 (1.60)

$\mu(ddif)$ is the average of daily difference between the return of each strategy and the buy-and-hold strategy. The numbers in the parentheses are the *t*-statistics testing whether the average daily difference is greater than zero. Asterisks imply significant at the 5 percent level or less for one-tail test, $t_{crit., 0.05}$ =1.645.

However, we must consider risk and transaction costs of each strategy in order to choose the best rule/strategy. Table 5 reports the one way "break-even" transaction costs and the risk of various MA rules for the above four strategies. The one-way break-even transaction cost (BEC) eliminates the extra return from MA trading rules. Following Bessembinder and Chan (1995), we estimate the one way BEC by adding the daily excess returns (Beyond B&H) produced by each trading rule and strategy over the 11423 days and then divide it by the number of trades over the entire period. Since Strategies 2 and 4 imply shorting the NASDAQ index, we divide the sum of the daily excess return by 2 times the number of trades. We also assume that investing in a money market does not incur any transaction cost. The estimation of risk is the standard deviation of daily returns of each strategy which should be compared with the daily standard deviation of B&H strategy of 1.23 % in Table 2 for the entire period.

Table 5 provides BEC and risk of each trading rule and various strategies; the first number in each cell is the BEC and the second number is risk, both in percent. Strategy 1 has an average risk of 0.76 % much lower than the B&H risk of 1.23 % of Table 2. The risk of Strategy 2 is similar to the risk of the B&H strategy. Finally, the average risk of the Strategies 3 and 4 are 1.51% and 1.80% respectively, both higher than the risk of B&H strategy. In comparison, Strategy 1 is superior to Strategies 2 due to its higher BEC and lower risk. The risk and return trade-off implies that if a trader prefers a lower-than-market risk, then Strategy 1 in combination with MA-100 or MA-150 or MA-200 would be the best trading rules with BEC of 0.22, 0.24, and 0.29 percent. On the other hand, if a trader has a little higher risk tolerance, then Strategy 3 is superior to Strategies 4, since strategy 3 implies lower risk and higher BEC than Strategies 4. Strategy 3 with either MA rules of 100, 150, or 200 days will provide profitable trading if transaction cost of trading NASDAQ composite ETF is less than 0.29 %. In conclusion, MA-100, MA-150, and MA-200 associated with Strategies 1 and 3 serve as the most profitable choices for traders.

Table 5: Break-Even Costs and Risk of Various Strategies

	Strategy 1	Strategy 2	Strategy 3	Strategy 4
MA-20	0.10/0.75	0.09/1.23	0.15/1.49	0.11/1.78
MA-50	0.15/0.75	0.12/1.23	0.20/1.50	0.15/1.79
MA-100	0.22/0.74	0.17/1.23	0.29/1.49	0.21/1.78
MA-150	0.24/0.76	0.19/1.23	0.33/1.52	0.23/1.80
MA-200	0.29/0.79	0.22/1.23	0.38/1.57	0.26/1.83

The break-even cost (BEC) estimated by dividing total daily excess returns into total number of trades over the entire period from 1972-2015. Risk is the standard deviation of daily returns. In each cell the first number is the BEC in percent and the second number is risk in percent. Each cell shows (BEC/Risk).

To test the robustness of results, we divide the entire sample into four sub-periods and provide the estimated BECs for Strategies 1 and 3 for MA-100, MA-150, and MA-200 in Table 6. Table 6 presents the risk and BECs of our best three rules for four sub-periods. The risks (standard deviation of returns) of the B&H strategy are 0.761 %, 0.856 %, 1.795% and 1.332 % for four sub-periods respectively. The BECs are estimated the same way, by dividing total excess return over the B&H strategy into the total number of trades in each sub-period.

Noted in Table 6, the BEC are relatively high in the first three sub-periods for both Strategies 1 and 3. Compared with the risk of B&H in each period, Strategy 1 again has a lower risk in each sub-period with high BEC in the first three sub-periods. Strategy 3 has a bit higher risk in each sub-period than B&H but has very high BEC implying strong possibility of profitable trading. A trader with a bit more risk tolerance than B&H would adopt MA-100 with combination of Strategy 3 to gain higher BEC in each sub-period, including the fourth sub-period. For risk-averse choice, a trader could apply MA-100 with Strategy 1 and gain very well in the first 3 sub-periods but would lose not much (since BEC is a small negative number) in the fourth sub-period. Our findings also partially echo Feng et al (2013) to indicate that MA trading rules have not been very successful recently, since the publication of BLL.

In order to see whether other well-known trading rules can do as well as moving average rules, we apply two addition popular indicators to NASDAQ composite index. The Relative Strength Index (RSI) indicator, which measures the velocity of directional movement by providing the internal strength of a single security or index, was created by Wells Wilder (1978). Wilder suggests using 14 days for estimating the RSI's value which ranges from 0 to 100. In this study we use two variants of RSI trading as follow:

I. In the market if RSI >50;
   Out of the market if RSI ≤ 50.

II. Many traders believe if RSI is above 85 it implies that the market is overbought and if it is below 15, then the market is oversold. Thus RSI model 2's rules are as follow:

   In the market if: 50 ≤ RSI ≤ 85 or if: RSI ≤ 15;
   Out of the market if: 15 < RSI <50 or if RSI > 85.

Table 6: Break-Even Costs and Risk of Various Strategies

	Strategy 1					
	MA-100		MA-150		MA-200	
Sub-Period	**BEC %**	**RISK %**	**BEC %**	**RISK %**	**BEC %**	**RISK %**
1/72 – 12/84	1.63	0.48	2.46	0.50	1.72	0.51
1/85 – 12/94	0.89	0.56	0.67	0.56	0.39	0.57
1/95 – 12/04	0.34	1.06	0.20	1.10	0.51	1.16
1/05 – 10/15	-0.09	0.78	-0.35	0.79	-0.32	0.81
	Strategy 3					
Sub-Period	**BEC %**	**RISK %**	**BEC %**	**RISK %**	**BEC %**	**RISK %**
1/72 -12/84	2.74	0.99	4.1	1.00	2.75	1.02
1/85 – 12/94	2.54	1.11	2.26	1.13	1.74	1.14
1/95 – 12/04	1.27	2.13	1.04	2.19	2.01	2.31
1/05 – 10/15	0.34	1.56	-0.24	1.59	0.04	1.61

Results for four sub-periods. BEC is the break-even cost, estimated by dividing total daily excess returns for each sub-period into total number of trades in that sub-period. Risk is the standard deviation of daily returns in each sub-period.

The second popular indicator allied to NASDAQ Composite is the Histogram based on Gerald Appel's (1980) Moving Average Convergence Divergence (MACD), Stochastic. MACD is the difference between two exponential moving averages (EMA). We follow the Appel's recommendation and use 26 and 12 day EMAs. A 9-period EMA of the MACD (the signal line) is then plotted on top of the MACD. The trading rule is as follow: in the market if MACD is above the signal line and out of the market if MACD is below signal line. In Table 7 we present the results for the above three models, two based on RSI and on one MACD rules.

Table 7: Statistical Results for RSI and MACD Rules

	NASDAQ Composite Index							
Rules	**Buy**	**Sell**	**Buy-Sell**	***SDb***	***SDs***	n_b	n_s	**No. of Signals**
RSI-1	0.00091 (3.64)*	-0.00219 (-10.04)*	0.00310 (12.45)*	0.00938	0.01473	7029	4394	983
RSI-2	0.00088 (3.37)*	-0.00050 (-3.23)*	0.00138 (5.38)*	0.00964	0.01540	6842	4581	1113
MACD	0.00065 (1.76)	-0.00130 (-8.27)*	0.00195 (9.17)*	0.01065	0.01202	5789	6534	859

Results are for daily data from 1972-2015. n_b and n_s are the number of buy and sell days, SD_b and SD_s are standard deviation of buy and sell days respectively. The numbers in the parentheses are the t-statistics testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero. Numbers marked with asterisks are significant at the 5% level for a two-tailed test, $t_{crit., 0.05}$ =1.96.

The results of Table 7 strongly support the predictive power of RSI and MACD trading rules; all buy minus sell t-statistics are highly significant rejecting the hypothesis that the mean buy days is equal to the mean sell days. In Table 8 we report the average buy minus sell days for each sub-period with their corresponding t-statistics.

Table 8: Mean buy minus mean sell for each sub-period

	Sub-Period 1	Sub-Period 2	Sub-Period 3	Sub-Period 4
RSI 1	(12.73)*	(7.72)*	(5.74)*	(3.02)*
RSI 2	(5.38)*	(4.28)*	(2.48)*	(-0.97)
MACD	(9.47)*	(6.32)*	(3.34)*	(2.80)*

Mean buy minus mean sells are the difference of average buy days minus average of sell days for each sub-period. The numbers in the parentheses are the t-statistics testing the difference of buy-sell from zero. Numbers marked with asterisks are significant at the 5% level for a two-tailed test, $t_{crit., 0.05}$ =1.96.

Again, Table 8 concludes a very strong predictive power of technical trading. All except one buy minus sell averages are highly significant rejecting the equality of mean buy days with mean sell days. This conclusion does not support the efficiency of NASDAQ composite index.

4. Conclusion

In this paper, we investigate a few moving average trading rules for the NASDAQ Composite index over the period of 1/3/1972 to 10/14/2015. Overall our results strongly support the predictive power of MA trading rules for NASDAQ. Almost all the buy-sell differences are significantly positive to reject the null hypothesis of equality of buy days returns with sell days returns for NASDAQ. For NASDAQ, the t-statistics for most buy and most sell are significant, rejecting the null hypothesis that the mean buy and sell returns equal to the mean of B&H returns. Therefore, we can conclude that MA rules have predictive power for NADAQ composite index.

To investigate the most profitable strategies for MA rules for NASDAQ when considering both transaction costs and risk, we design a total of 4 strategies to test the significance and robustness in profitability. There are two driftnet risk tolerance strategies found to be very profitable when using MA-100 in NASDAQ. For risk-averse investors, Strategy 1, in which a trader will be in NASDAQ when MA-100 emits buy signals and be in the money market when MA-100 emits sell signals, is the choice to beat the B&H strategy for entire period (BEC of 0.22 %, and a risk lower than B&H) and 3 out of 4 sub-periods with very high BECs. For a more risk-taker trader, applying MA-100 with Strategy 3 (i.e. a bit more risk than B&H) leveraging at money market rate for buy days and being in the money market for sell days, can beat handsomely the B&H for the entire period and each sub-period. Finally we apply two very popular indicators (RSI & MACD) to NASDAQ composite index and find that both also have very strong predictive power for entire period and each sub-period. We would note that both RSI and MACD trading rules imply more in and out of the market than MA 100, therefore traders with higher transaction costs should be careful to apply these trading rules.

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