Talking Numbers:

Technical versus Fundamental Recommendations

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Abstract:

This study assesses the economic value of technical and fundamental recommendations simultaneously featured on "Talking Numbers," a CNBC and Yahoo joint broadcast. Technicians display stock-picking skills, while fundamentalists reveal no value. In particular, technicians overwhelmingly outperform fundamentalists in predicting returns over horizons of three to nine months and moreover they produce large alpha with respect to the Fama and French (1993) and momentum benchmarks. Considering market indexes, Treasuries, commodities, and various equity indexes, both schools of recommendation generate poor forecasts. Overall, the evidence shows that proprietary trading rules could, at best, enhance investments in single stocks, while returns on broader assets are unpredictable.

Keywords: fundamental analysis; technical analysis; market efficiency; abnormal returns

JEL Codes: G10, G14, G24

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1. Introduction

This paper employs a novel dataset from "Talking Numbers" to assess the economic value of technical and fundamental recommendations covering a comprehensive list of assets. Hosted by CNBC and Yahoo Finance, "Talking Numbers" is a media broadcast simultaneously featuring fundamental and technical recommendations before and during the market open. Dual recommendations are made by highly experienced analysts representing prominent institutions. This unique setup featuring synchronized recommendations, multiple assets, and the presence of leading professionals, offers important insights in assessing the value of financial analysis.

For one, we establish a natural experiment to contrast technical and fundamental analyses and gauge the real time value of dual recommendations. Our experiments are robust to several biases characterizing analysts' forecasts. To wit, as the bar to participate in the show is high, analysts are less prone to career concerns, and, moreover, the simultaneous broadcast eliminates potential cross-herding between analysts. Next, analysts' recommendations span individual stocks and broader assets, including Treasuries, commodities, domestic and foreign market indexes, and various equity indexes. During the broadcast, both schools of thought are essentially exposed to the same public information. Thus, comparing performance enables one to assess the extent to which technicians and fundamentalists efficiently process the flow of public information.

Our analysis is reasonably robust to data mining concerns. Indeed, to our knowledge, we are the first to visit the fundamental and technical recommendations broadcasted in "Talking Numbers," and moreover, we explicitly study technical recommendations rather than technical rules, which are at the core of the literature on technical analysis. Finally, analyst' recommendations feature the largest stocks (e.g. Apple, Google, Exxon Mobil), liquid commodities (e.g. gold, oil), main exchange rates (e.g. the US dollar), major bonds (e.g. the U.S. ten-year notes), major indices (e.g. the various Dow Jones indexes), and prominent sectors (e.g., Technology, Real Estate, Pharmaceutical). In addition, our experiments are comprehensive employing 1000 dual recommendations on 262 stocks and 620 dual recommendations on the other assets. Thus, our findings are general enough and are less prone to liquidity concerns.

Figure 1 highlights the major empirical evidence for technical and fundamental stock recommendations during the sample period from November 2011 to December 2014. Plotted are the Cumulative Abnormal Returns (CARs) starting from the recommendation broadcast (Panels A and B) and the cumulative payoffs generated by four spread portfolios (Panel C) undertaking long (short) positions in stocks with buy (sell) recommendations. In particular, we consider buy-minus-sell and strong buy-minus-sell, both technical and fundamental, spread portfolios.

[Please insert Figure 1 here]

The evidence shows that technicians display rather impressive stock-picking skills, while fundamentalists provide no value, whatsoever. To illustrate, observe from Panel A that the nine-month CARs of the strong sell, sell, hold, buy, and strong buy technical recommendations are $-8.85\%, -2.74\%$, -0.02%, 1.74%, and 7.92%, respectively. In contrast, Panel B shows that CARs attributable to fundamental analysis do not align with the type of recommendation. If anything, sell recommendations generate higher CAR than the buy recommendations.

Similarly, observe from Panel C that the value of the fundamental buy-minus-sell portfolio is non-positive throughout the entire sample period, and the value of the fundamental strong-buy-minus-sell portfolio rotates around zero. In contrast, the value of the two corresponding technical portfolios is positive and it typically increases with the investment horizon. Over the sample period, the buy-minus-sell portfolio value is $0.42 per $1 initial long and \$1 initial short positions, recording annual alpha of 14.6% (t = 2.32). More prominently, the value of the strong buy-minus-sell portfolio is \$2.30, recording strikingly large annual alpha of 45.3% (t = 3.58). Considering trading costs upon entering and exiting a position, the threshold cost that would set the alpha of the buy-minus-sell (strong buy-minus-sell) portfolio to zero is 0.82% (3.08%) per transaction.

We find that technical analysis outperforms along two dimensions. First, it generates a higher proportion of correct recommendations, where a correct recommendation amounts to buy (sell) recommendations followed by advancing (diminishing) stock prices. Second, technical recommendations record higher gains following correct recommendations and lower losses following incorrect recommendations. The success of technicians in picking stocks is robust to controlling for common risk factors as well as for firm-level size, book-to-market ratio, volatility, trading volume, and past trends in stock prices. It is also unaffected by analyst's gender, by the immediate impact of the broadcast on stock price (which is found to be highly significant), and, as shown earlier, by reasonable trading costs.

We further demonstrate that the inability of fundamentalists to predict future returns is uniform across all industries and styles considered. In contrast, technical stock recommendations produce robust predictions for all styles and industries, excluding mining. The failure to predict returns on mining stocks mirrors the inability of all analysts, participating in "Talking Numbers," to predict future commodity prices. In fact, both schools of thought have been unable to predict returns not only on commodities but also on the other broader assets, e.g., Treasuries, market indexes, and industries. The difference in performance among individual stocks versus broad indexes is possibly due to arbitrage capital in that investable patterns in broad market indexes immediately attract capital and are thus traded away. Moreover, common wisdom suggests that the abilities to efficiently process public information or to extract private signals from prices and volume mostly characterize individual stocks while they are less appealing to broader assets.

Three strands of studies are related to our work. The first investigates the value of fundamental recommendations. Jegadeesh et al. (2004) find that the level of analysts' consensus recommendation provides little value over other investment signals. Stickel (1995) and Womack (1996) document value in revisions in consensus recommendations, while Barber et al. (2001) display the disappearance of that value in the presence of transaction costs. Likewise, Metrick (1999) and Jaffe and Mahoney (1999) exhibit the lack of forecasting value focusing on comprehensive samples of investment newsletters. Here, we show that even considering the elite group of analysts, appealing to the large crowd, fundamentalists provide no investment value.

The second strand deals with technical rules. Theoretically, Brown and Jennings (1989) and Blume et al. (1994) show that past prices and trading volume, respectively, could reveal the presence of private information, and Zhu and Zhou (2009) show that combining moving average with other technical signals improves asset allocations. Empirically, the evidence on the strength of technical analysis is mixed. Brown et al. (1998) show that Dow rules exhibit predictive ability, yet trading frictions could consume profitability. Brock et al. (1992) find that technical rules predict returns on stock indexes. However, such predictability becomes nonexistent in the presence of transaction costs, per Bessembinder and Chan (1998). Sullivan et al. (1999) and Allen and Karjalainen (1999) do not find substantial value in technical rules, while Lo et al. (2000) show that technical patterns predict individual stock returns. Han et al. (2013) apply moving average to equity portfolios and report profitability, and Neely et al. (2014) show that technical indicators exhibit predictive power for the equity premium. Notably, our paper assesses the value of technical recommendations rather than the value of publicized technical rules.

The third strand examines the immediate impact of media publicized recommendations. Mathur and Waheed (1995), Liu et al. (1990), and Barber and Loeffler (1993) document abnormal returns shortly after the publication of recommendations in the newspaper, and Hirschey et al. (2000) report abnormal returns on the day after the recommendations are posted on the internet. However, Dewally (2003) detects no market reaction to recommendations posted by newsgroup on the internet. Neumann and Peppi (2007) find that recommendations made by Jim Cramer, the host of the CNBC "Mad Money" program, are followed by abnormal payoffs during the following day, and Busse and Green (2002) find that recommendations broadcasted in the CNBC "Morning Call" and "Midday Call" programs produce abnormal immediate profits within 15 seconds. Relative to these studies, we examine the value, rather than the immediate impact, of recommendations. Eventually, technical stock recommendations provide value not only for an immediate trading, but also for a few months following the broadcast.

Indeed, to our knowledge, we are the first to compare head-to-head the quality of fundamental and technical analyses. Our setup is unique in that both schools of thought are exposed to the same public information, simultaneous recommendations are made by well-positioned analysts, and the collection of assets covered is comprehensive. A remaining task is to shed light on the economically large alpha delivered by technical stock recommendations. In active asset management, alpha reflects stock picking and benchmark timing skills, where stock-picking skills could further be attributable to industry or style rotation. Economic theory (e.g., Admati et al. 1986) typically formulates skills through managerial ability to process private signals. Empirically, however, one cannot conclude whether a positive-alpha manager does possess private information or perhaps that manger has the ability to process public information more effectively. Of course, there has always been the bad-model concern. In particular, performance specifications may improperly account for those factors characterizing the risk-return tradeoff and further they are likely to misspecify the nature of time variation in both benchmark loadings and benchmark risk premiums. Similar issues and concerns apply in our context. Essentially, we rule out the possibility of market timing and industry or style rotation, as technicians fail to predict returns on broad indexes. Putting aside bad model concerns, technicians could indeed use private signals as prescribed by theory. Alternatively and perhaps more convincingly, technicians may process public information more effectively through their investment toolkits. Pinning down the exact source of stock picking skills in a general context is a worthy research agenda for future work.

The remainder of the paper is organized as follows: Section 2 presents the data and methodology. Section 3 reports the empirical results corresponding to individual stocks. Section 4 extends the analysis to other asset classes noted earlier. Section 5 concludes. The list of assets and the recommendation classification system are given in the appendices.

2. Methodology and Data

Our technical and fundamental recommendations are extracted from the media broadcast entitled “Taking Numbers.” Prior to May 2013, the program was exclusively hosted by the CNBC television network. From May 2013, CNBC and Yahoo Finance have been jointly hosting the show. Based on Yahoo, the broadcast “takes a 360° approach to trading-highlighting the best investment opportunities by analyzing stocks both a technical and a fundamental point of view…” A typical broadcast features assets that make headlines in the financial media. Examples include stocks of prominent firms that are about to post financials, hot sectors, hot markets, and general assets experiencing substantial price changes (e.g., the recent drop in commodity prices and the rise in the U.S. dollar).

Fundamental analysis typically starts with a macroeconomic outlook, industry conditions, and then a recommendation follows along with supporting discussions. Technical analysis, in most cases, describes a chart of historical prices along with moving averages. The analyst then discusses the main technical characteristics underlying the recommendation. Often, there are more supporting charts and even a discussion linking the technical recommendation to fundamental factors. It is common that the technical analyst, the fundamental analyst, and the show hosts debate the nature of the recommendations.

The sample spans November 8, 2011 through December 31, 2014. November 8, 2011 featured the first comparison between technical and fundamental points of view. Beforehand, "Talking Numbers" was a rather different show. It was part of the CNBC broadcast "Closing Bell", and usually featured the view of a single analyst who mainly discussed the S&P 500 index. In the first year of the sample, the program was broadcasted once per trading day, typically featuring four recommendations: two distinct assets each of which is covered by both technical and fundamental analysts. More recently, the program has usually been broadcasted several times daily while in most cases each program covers a single asset. In a few cases, the program features only one analyst delivering either technical or fundamental recommendation without a counter view. Such single recommendations are excluded from the primary analysis and are later considered for examining the robustness of results.

Prior to CNBC's merge with Yahoo in May 2013, we approached the broadcasts using two main sources: the CNBC archive at video.cnbc.com and The Internet Archive's TV news research service at archive.org. For that period, we employ several net searching practices to detect programs that were missing from the main data archives. After the merge, the main source is Yahoo Finance at finance.yahoo.com. This source is organized chronologically and contained all the post-merger programs. Overall, we cover the vast majority, if not all, of "Talking Numbers" shows during the sample period.

We classify technical and fundamental recommendations into five conventional categories, i.e., "strong buy", "buy", "hold", "sell," and "strong sell." In about 20%–30% (depending on the asset class) of the cases, the analyst's formal rating is explicitly stated verbally or in a caption. Then, the classification clearly adheres to analysts' explicit ratings. In other cases, the recommendation is not explicit. Then we systematically extract the recommendation category based on the content of the show, as discussed in the next paragraph. We viewed each program twice and classified separately into each of the five recommendation categories. In most cases, the two classifications were identical. If a mismatch emerged the program was viewed again and the final classification was then delivered.

Appendix A provides the full list of terms characterizing the five recommendation categories, while Appendix B illustrates how classification is made for specific program. Below we provide a comprehensive discussion.

The strong buy category features distinct and enthusiastic recommendation to buy an asset without any reservation. Any expectation for at least 20% gain during the coming year (expressed directly or implied by the analyst's price target) falls within this category. The buy category characterizes a buy recommendation with reservations that do not deter from immediately buying the asset, a clearly positive business forecast, and the use of positive terms such as "cheap" and "overweight". For example, if an analyst suggests to start buying the asset and increase buying as a pullback emerges, such explicit recommendation would be classified as a buy. However, if an analyst recommends to wait for a pullback and only then buy the asset, that contingent recommendation would be classified as a hold.

The strong sell category consists of distinct recommendations to immediately sell the asset without any reservation, which is occasionally even accompanied by a suggestion to sell it short. Any expectation of at least 20% price drop during the coming year falls within this category. The sell category features a sell recommendation with reservations that do not deter from immediately selling the asset, a clearly negative business outlook, a distinct “do not buy” statement, and the use of terms such as “underperform” and “overbought.”

The hold category consists of all recommendations to hold the asset or recommendations featuring assets as “market perform” and “neutral”. To avoid subjective judgment biases and misinterpretation, we attribute to the hold category mixed, contingent, ambiguous, and contradicting recommendations. This classification guarantees that the buy and sell categories are unambiguous and transparent.

While differences between strong buy and buy and between strong sell and sell recommendations could be subtle, distinctions between buy and sell groups are clear and well defined. It is unlikely that a positive recommendation would be classified as a sell or a negative recommendation would be classified as a buy. Notably, the main results are qualitatively similar whether we employ the five-category scale, a three-category scale (all buy, hold, and all sell), as well as a two-category scale (all buy and all sell, excluding hold).

Several additional notes are in order. First, we consider only recommendations corresponding to “investment” horizons, ranging from a few months to one year which are provided in all the programs. Yet, in a few programs, analysts also provide a separate one-day or a few days’ time-horizon recommendation, usually referred as a “trading” recommendation.

Even less common, in a few cases analysts also provide a long-term forecast for horizons longer than one year (usually three to five years). Such recommendations are exceptional items. Moreover, they are always provided along with the recommendation for the main investment horizon and are usually provided by a single analyst. We discard short-term and long-term recommendations. Second, while discussions about the market index (S&P500) often include both negative and positive aspects and tones, single stock discussions are more distinctive and clear with technical discussions typically being more transparent and strict than fundamental ones.

Table 1 summarizes descriptive statistics of the broad set of recommendations for single stocks, the market index, particular sectors, bonds, commodities, and currencies. Appendix C describes the full list of all individual stocks featured in "Talking Numbers" as well as all other assets. Altogether, we have been able to capture 1620 dual recommendations, as detailed below. There are 1,000 technical recommendations and 1,000 fundamental recommendations (1,000 dual recommendations) featuring 262 individual stocks. There are 149 dual recommendations covering the S&P500 index (the NYSE Composite index in one case); 256 dual recommendations corresponding to 58 indices and ETFs, such as the NASDAQ 100, the DOW JONES Industrial/Utilities/Transportation, particular sectors including banking, retail, homebuilders, miners, and biotechnology, as well as non-U.S. markets including emerging markets, frontier markets, and the Nikkei 225; 50 dual recommendations featuring bond yields (mostly ten-year Treasuries but also municipal bonds); 144 dual recommendations about 17 commodities (especially gold and crude oil); and 21 dual recommendations covering exchange rates between the U.S. dollar and three other currencies and one basket of currencies. In 370 shows, a single recommendation records no corresponding comparison, because either there was only one analyst participating in the show or one of the analysts did not ultimately discuss the relevant asset. As noted earlier, such recommendations are excluded from the main analysis but are later considered in robustness tests. There are 28 observations which are excluded because the underlying asset is unique (e.g., Bitcoin).

Observe from Table 1 that while among general asset classes the number of technical and fundamental analysts is quite similar, it is markedly distinct among single stocks. There are 34 technical versus 159 fundamental analysts. The smaller number of technicians covering stocks could be attributable to their reasonably successful predictions, as shown below, which would encourage the program directors to keep them. Also notable is the relatively small number of fundamental and technical female analysts—about 10% across all the various asset classes. While among the asset classes, recommendations span all five categories, there are substantially more buy and sell recommendations than strong buy, strong sell, and hold recommendations.

The Spearman rank correlation coefficient, which measures the correlation between the one through five figures (e.g., 1 stands for strong sell) corresponding to the fundamental and technical recommendations, is typically small. It is 0.05 for single stocks, 0.18 for the market index, 0.21 for sectors and non U.S. indices, 0.29 for bonds, and 0.38 for commodities. Technical and fundamental recommendations are closely related in predicting exchange rates, recording Spearman correlation coefficient of 0.51. Likewise, the Person's Chi-squared statistic strongly rejects the hypothesis that technical and fundamental recommendations for exchange rates differ to significant degrees.

We next discuss the sources of finance, accounting, and economic data used in the empirical analysis to assess the quality of recommendations. Stock return and trading volume figures are from the Center of Research in Security Prices (CRSP). Firm accounting variables such as book value are from CUMPUSTAT. Earnings surprises are based on the Institutional Brokers' Estimate System (I/B/E/S). The Fama and French and momentum factors, used to risk-adjust investment returns, are provided by Kenneth R. French's library. Stock indices covered by "Talking Numbers" are provided by the S&P Dow Jones Indices, NASDAQ OMX Global Indexes, Nikkei, Moscow Exchange, Bucharest Stock Exchange, and International Securities Exchange (Homebuilders Index).

Prices of precious metals are provided by The London Bullion Market Association. Natural gas prices are from the U.S. Energy Information Administration (EIA). Coper prices are provided by the New York Mercantile Exchange. Agriculture prices are provided by CME and Intercontinental Exchange (ICE). The CRB Index is provided by Thomson Reuters. All other commodity prices are from The Federal Reserve Bank of St. Louis. Exchange rates are also from the Federal Reserve Bank of St. Louis with the exception of the ICE Dollar Index which is provided by ICE.

Interest rates are also provided by the Federal Reserve Bank of St. Louis. The 90-day treasury-bill rate serves us as a proxy for the risk-free rate. To measure performance of ten-year bond recommendations we employ two methods. First, the ten-Year Treasury Constant Maturity Rates are used to calculate the price of a notional zero-coupon ten-year bond. Second, we employ the price of the iShares 7-10 Year Treasury Bond ETF. As the empirical evidence for both methods is similar, we report findings for the first approach.

3. Individual stocks: the empirical evidence

This section exclusively focuses on single stock recommendations. The other asset classes, i.e., commodities, market-wide indices, sectors, and currencies, will be analyzed in the next section. Figure 2 depicts average stock returns for the five recommendation categories. Womack (1996) and Jegadeesh and Kim (2004) report a drift in prices lasting between one and six months after a recommendation revision. Here, we consider similar investment horizons of one, three, six, and also nine months following the broadcasts. Left (right) figures pertain to fundamental (technical) analysis. Top figures exhibit raw average returns while bottom figures display returns adjusted for the three Fama-French (1993) and momentum factors.

Consistent with findings reported in the introduction, it is evident from Figure 2 that fundamentalists have not been successful in predicting stock returns. The mean raw returns during one, six, and nine months following sell recommendations are actually higher than mean returns following buy recommendations. For the nine-month horizon, mean returns associated with sell and buy recommendations are 18.39% and 13.79%, respectively. The corresponding risk adjusted figures are 2.80% and 0.27%. In contrast, the technical analysis reveals rather strong return-recommendation relation. Focusing on the six-month horizon, average returns are 3.65% (strong sell), 7.25% (sell), 11.77% (hold), 10.81% (buy), and 16.84% (strong buy). The risk adjusted figures are -5.20% (strong sell), -1.78% (sell), 2.57% (hold), 1.76% (buy), and 5.46% (strong buy).

[Please insert Figure 2 here]

Table 2 reports the relation between investment average return, recommendation category, and the investment horizon in more detail. We report average returns for the five recommendation types. Moreover, as the classification to “all buy” (buy and strong buy recommendations) and “all sell” recommendations (sell and string sell recommendations) is fairly unambiguous, we also report returns corresponding to such “all” categories.

Starting from the fundamental analysts, sell recommendations are followed by higher average returns than buy recommendations for one, six, and nine-month horizons. For instance, for the nine-month horizon, sell (buy) recommendations record 18.4% (13.8%) average return. Comparing strong buy and strong sell fundamental recommendations reveals more appealing outlook. Return spreads between the two extreme categories are 1.3%, 5.0%, 7.8%, and 11.2% for the four investment horizons. Such spreads may appear inconsistent with the payoff description (Figure 1c) of the strong buy-minus-sell portfolio. Notice, however, that prior to August 2013 there were no records of strong sell recommendations. For the next few months afterward, there was a single such recommendation followed by a big loss due to a substantial advance in the corresponding stock price. The payoff description (Figure 1c) of the fundamental strong buy-minus-sell portfolio is largely impacted by the rare appearance of fundamental strong sell recommendations, during the beginning of the sample.

Nevertheless, our overall findings are consistent in that the return spread between all buy and all sell fundamental recommendations are relatively small given by 0.1%, 1.4%, and 0.4% and -1.1%, respectively. Likewise, for all sell and all buy fundamental recommendations, the Mann-Whitney test reveals that the return distributions are indistinguishable, implying that the fundamental analysis is comparable with random draws of recommendations.

In contrast, technical analysis reveals impressive stock-picking skills. Their buy recommendations predict uniformly higher average returns, both raw and risk adjusted, than sell recommendations. For instance, for the nine-month horizon, buy and sell recommendations are associated with 17.0% and 13.8% average raw return, respectively. The corresponding risk adjusted figures are 2.5% and -0.6%. Further, return spreads between all buy and all sell recommendations are equal to 1.9%, 2.4%, 6.2% and 6.1% for the four horizons considered. Similar evidence emerges on the basis of risk adjusted returns. Investment returns following all buy recommendations are uniformly larger than all sell. For example, the corresponding nine-month returns are 19.4% and 13.3%.

All statistical tests pertaining to the technical recommendations are highly significant, indicating that the success of the technicians is not random. Specifically, among technical recommendations, the Kruskal-Wallis statistic (which is a non-parametric test for the equality of the mean return distributions) significantly rejects the null hypothesis of equal mean returns for the various categories of recommendations. Similarly, the Mann-Whitney statistic, which is a non-parametric test for the equality of all buy and all sell distributions, highly rejects the null hypothesis, implying that the distribution of returns realized following all buy recommendations is significantly different (shifted to the right) from that of all sell recommendations.

[Please insert Table 2 here]

Predictability's success can be assessed through the average return following the recommendation or the relation between the type of recommendation and the sign of future return regardless of its magnitude. Figure 3 reports the number of correct versus incorrect recommendations as well as the average return conditional on recommendations for the six-month horizon. A correct (incorrect) recommendation amounts to positive (negative) return following hold, buy, and strong buy recommendations or negative (positive) return following sell and strong sell recommendations.

[Please insert Figure 3 here]

Starting from raw returns (Figure 3a) out of 340 technical buy recommendations, 250 turn out to be correct while only 90 turn incorrect. Corresponding figures for fundamental analysts are 242 and 102. For both technical and fundamental analysts, the number of correct sell recommendations is substantially smaller than that of incorrect recommendations, while the numbers of strong sell correct and incorrect recommendations are nearly identical. Moving to risk-adjusted returns (Figure 3b), the number of correct technical recommendations is substantially larger than incorrect across all categories including sell (146 versus 117) and strong sell (46 versus 26). The corresponding fundamental figures are 150 versus 138 and 34 versus 30, respectively. A simple Sign test confirms the superiority of technical analysis. The null hypothesis of equal number of correct and incorrect technical recommendations is significantly rejected ($p < 0.01$) for all horizons, regardless of whether hold recommendations are included or excluded and regardless of whether all buy and all sell recommendations are considered separately. For fundamental recommendations, the null hypothesis is not consistently being rejected.

Overall, Figure 3 shows that technical recommendations generate more correct recommendations as well as higher investment returns. As noted, for buy recommendations, there are 250 technical correct recommendations (74%) versus 90 incorrect recommendations (26%), whereas there are 242 (70%) correct fundamental recommendations versus 102 (30%) incorrect recommendations. Moreover, the average return of buy correct recommendations is 19.6% (technical) versus 18.3% (fundamental). Similarly, the average return of incorrect buy recommendations is −13.7% (technical) versus −14.6% (fundamental). Aggregating figures, buy recommendations are followed by average return of (250×19.6%–90×13.7%)/340=10.81% (technical) versus (242×18.3%–102×14.6%)/344=8.59% (fundamental). Similarly, the performance figures favor technical recommendations among all recommendation categories, both for raw and risk adjusted returns. The advantage is apparent along two dimensions: the number of correct recommendation and the quality of recommendations manifested through higher gains following correct recommendations and lower losses following incorrect ones.

3.1 Cross-section analysis

Regression analysis is essential for further studying the quality of recommendations, as it allows one to control for firm attributes known to predict the cross section of future returns. In addition, in the context of analysts' recommendations it has been shown that firm size (Womack, 1996), past return, volume, the book-to-market ratio (Jegadeesh et al., 2004), and industry affiliation (Boni and Womack, 2006) are associated with performance of recommendations. In response, we run the cross section regression

$$R_i = \gamma_0 + \gamma_1 REC_i + \gamma_2 ME_i + \gamma_3 (BE_i / ME_i) + \gamma_4 VOL_i + \gamma_5 VOLUME_i + \sum_{j=1}^{3} \gamma_{6j} R_i^j +$$
$$\gamma_7 \Delta VOLUME_i + \gamma_8 \Delta VOL_i + \sum_{j=1}^{2} \gamma_{9j} RECIMPACT_i^j + \sum_{n=1}^{2} \gamma_{10j} SURPRISE_i^j + \varepsilon_i, \qquad (1)$$

where i is the stock-specific subscript, R_i is the investment return; REC_i describes the recommendation category (1-strong sell, 5-strong buy); ME_i is the previous year log of the market capitalization; BE_i is the previous year positive book value and zero otherwise; VOL_i is return volatility measured from daily returns over the year prior to the recommendation broadcast; $VOLUME_i$ is the log of the average daily trading volume over the year prior to the broadcast; $R_i^{j=1,2,3}$ denote returns during six months, one month, and two to four months prior to the recommendation broadcast; ΔVOL_i and $\Delta VOLUME_i$ are, respectively, the changes in volatility and volume during the last three months relative to the whole year prior to the broadcast; $RECIMPACT_i^{j=1,2}$ are the return and change in volume over two days following the recommendation broadcast, intended to control for any immediate impact of recommendations; and $SURPRISE_i^{j=1,2}$ are the percentage surprises in earning per share during the past two quarters.

Table 3 reports the regression evidence. We consider 15 distinct tests. The dependent variable in most tests (unless otherwise noted) is the six-month return following the broadcast. Test 1 excludes all control variables. Here, consistent with previous analyses, the fundamental recommendations' (REC_i) coefficient is insignificant while the technical counterpart is significantly positive (t = 6.80). Test 2 considers the past six months return as a control variable. While past return enters significantly, the technical recommendations' coefficient is still significantly positive (t = 5.48). Likewise, unreported regressions confirm that technical recommendations are significantly positively correlated with past returns corresponding to horizons ranging from one to seven months. Nevertheless, trend following by itself does not capture the ability of technical analysts to deliver reasonably robust predictions.

Tests 3 controls also for size, the book-to-market ratio, volatility, and volume. The evidence supporting technical recommendations is still profound. Notice that our sample consists of large firms mostly belonging to the upper size decile, with an average market capitalization of 39 billion dollar, and medium book-to-market firms belonging to low-mid book-to-market deciles (see Appendix C for the list of stocks). Thus, it may not be surprising that our sample of stocks does not exhibit effects related to size, volatility, or the book-to-market ratio. Indeed, all additional control variables are insignificant.

[Please insert Table 3 here]

Test 4 accounts also for past returns over various periods, change in volume and volatility in the last three months, earnings surprises, as well as controls for the potential immediate impact of the recommendation broadcast on stock return and trading volume. Again, fundamental recommendations do not display economic or statistical significance, whereas technical recommendations are positively associated with future stock returns (t = 3.48).

Controlling for various past stock return variables does not capture the predictive power of technical recommendations. The return-recommendation relation is also not attributable to the direct short-term impact of the broadcasts on stock prices and trading volume even when the coefficients corresponding to these two variables are significant. While there is a significant immediate impact of recommendations on stock price and trading volume, the predictive ability of technical recommendations persists long afterwards (see in particular the evolution of investment payoffs displayed in Figure 1).

Tests 5 and 6 mirror Tests 3 and 4, respectively, except that the dependent variable is six-month return adjusted to Fama-French and momentum factors. Evidently, the predictive ability of technical recommendations is unexplained by common risk factors that could simultaneously affect stock prices and the recommendation category.

Our sample consists of relatively homogenous group of "elite" analysts. This mitigates potential systematic biases involving analysts' experience and reputation (Graham, 1999; Sorescu and Subrahmanyam, 2006) as well as career concerns (Hong, et al. 2000; Clement and Tse, 2005). Moreover, Kumar (2010) shows that female analysts display superior forecast ability due to self-selection process. Presumably, those females who have superb abilities as analysts pursue a career in a male-dominated industry. In our sample there are about 90% male analysts among fundamentalists and technicians across all asset classes (see Table 1). Thus, gender does not seem to establish a potential source for systematic bias.

Nevertheless, Test 7 implements a formal test accounting for analyst gender. The fundamental recommendations' coefficients are near zero and insignificant regardless of the analyst's gender. The technical recommendations' coefficients are relatively larger and highly significant (t = 5.10 for male and 3.47 for female). While the coefficient corresponding to female analysts is slightly larger (0.029 versus 0.024), gender effects are altogether insignificant. In sum, the success of technical recommendations in predicting returns on individual stocks are not captured by the analyst's gender effect. Moreover, female technical or fundamental analysts do not outperform male analysts.

While the dependent variable in Tests 1 through 7 is stock return (raw or risk adjusted) over six months following the recommendation broadcast, we also examine one, three, and nine month investment returns following the broadcasts. Tests 8 through 10 report the empirical evidence. For all investment horizons, fundamental recommendations' coefficients are indistinguishable from zero, while the technical counterparts are positively significant.

The remainder tests in Table 3 display the robustness of results focusing on six-month returns. Test 11 excludes the hold category to avoid potential misclassification errors. Indeed, the difference between buy and sell recommendations is more distinctive from the difference between hold and buy or hold and sell recommendations. Similarly, the difference between buy and sell recommendations is more distinctive from the difference between buy and strong buy and between sell and strong sell recommendations.

Test 12 focuses on all buy and all sell categories. As noted earlier, all buy is composed of both buy and strong buy recommendations, while all sell is composed of both sell and strong sell recommendations. The evidence again shows that the fundamental recommendations' coefficients are insignificant, while the technical recommendations' coefficients are highly significant (t = 5.71 and t = 4.12, respectively). That is, the results are robust to possible classification errors. They persist when the hold category and the distinctions between strong buy and buy and between strong sell and sell are excluded.

Tests 13 and 14 examine the sensitivity of results to the presence of outliers. The dependent variable in Test 13 is the six-month return winsorised at 2.5%. In Test 14 we employ the quantile regression around the median (τ = 0.5) which is less sensitive to extreme observations than the OLS regression. In both cases the technical recommendations' coefficients are highly significant (t = 5.88 and t = 3.45, respectively) suggesting that stock-picking skills of technical analysts to are not attributable to outliers.

Finally, a few programs featured a single, either fundamental or technical, recommendation with no comparison. While all reported tests exclude such programs, Test 15 accounts for single recommendation shows. The overall evidence is unchanged.

To summarize, cross-section regressions confirm the strong predictive ability of technical recommendations. That predictive ability is uncaptured by firm's size, the book-to-market ratio, volatility, volume, past stock trends, as well as by common risk factors, analyst's gender, and the potential direct impact of recommendation broadcasts on stock prices. The results are also robust to the presence of outliers as well as to potential classification errors. Fundamental recommendations, in contrast, do not exhibit clear and consistent relation with subsequent returns.

3.2 Examining industry and style effects

Boni and Womack (2006) argue that the economic value of financial analysts relates to analysts being industry specialists. To explore potential effects of industry affiliation and firm attributes on recommendations, we run the cross-section regression

$$R_i = \gamma_0 + \sum_j \gamma_{1j} (REC_i)(FIRM_{ij}) + \varepsilon_i, \qquad (2)$$

where R_i is the six-month stock return (we consider both raw and risk adjusted return) and REC_i describes the recommendation category (1-strong sell, 5-strong buy). We consider two specifications. In one, $FIRM_{ij}$ (j = 1,2,…,7) are dummies for seven industries: mining, construction and manufacturing, utilities, trade, financial and administration, and services. The industry division is made according to the Standard Industrial Classification (SIC) code with the exception that construction as well as wholesale trade and administration sectors, for which we record less than ten observations, are merged into their closest matching industries. In the second specification, $FIRM_{ij}$ (j = 1,2,3) are dummies for firms belonging to the bottom 30%, core 40%, and top 30% of either firm's size, the book-to-market ratio, volatility, or past return.

[Please insert Table 4 here]

Table 4 reports the results. Starting from the fundamental analysis, recommendations do predict future returns on the services industry. The mining coefficient is negatively significant while all other recommendation coefficients are generally insignificant. Moving to the technical front, excluding the mining industry, analyst recommendations produce robust predictions based on raw and risk adjusted returns. The failure to predict mining stock returns is consistent with the prominent inability of both technical and fundamental analysts to predict commodity prices, as we show below.

Panel B of Table 4 reports the impact of firm characteristics on recommendations. As the sample is dominated by large firms, we attribute the 19 firms belonging to the bottom group to the core group. The coefficients corresponding to size, the book-to-market ratio, volatility, and past return groups of fundamental recommendations are, for the most parts, insignificant. This is consistent with the notion that fundamental recommendations display low power in predicting future returns. In contrast, all coefficients corresponding to technical recommendations are highly significantly positive. The F statistics in the bottom of the table show that the predictive power of the technical analysis is higher for smaller cap and value firms, it is stronger for the core group of volatility relative to the two extreme groups, and it tends to be higher when returns during the previous year are lower.

4. Examining forecasts among broader asset classes

Why are technical recommendations successful in predicting returns on individual stocks? One possibility is that technicians trade on private signals, as prescribed by Brown and Jennings (1989), Blume et al. (1994), and Zhu and Zhou (2009). Common wisdom could suggest that private signals need not apply to broad assets, rather they mainly characterize individual stocks. Hence, we hypothesize that the value of proprietary investment toolkits relies on their ability to better refine private information from informed trading. The second possibility is that technicians could process public information more effectively through their toolkits. Also in that case the success of technicians may be more prominent among individual stocks as arbitrage capital is more invested in general assets and indexes thereby rather rapidly eliminating abnormal profits in those assets.

The empirical evidence provides support for these two potential explanations. In particular, Figure 4 presents the average returns on various asset classes for each school of thought. Left (right) plots feature fundamental (technical) recommendations. Asset classes include the S&P500 index (Figure 4a), sector/industry/non-U.S. indices (Figure 4b), U.S. bonds (Figure 4c), commodities (Figure 4d), and the U.S. dollar (Figure 4e). Further details of asset classes are provided in Appendix C. The four curves in each plot depict average returns over one, three, six, and nine months following the recommendation broadcast.

[Please insert Figure 4 here]

Briefly, Plots 4a through 4d show that both fundamental and technical analysts have been unable to predict the S&P500 index, sector/industry/non-U.S. indices, U.S. bonds, and commodities. Conversely, Figure 4e shows that both fundamental and technical recommendations impressively predict future currency rates, with the most outstanding positively monotonic curve corresponding to nine-month horizon.

Likewise, Figure 5 presents the cumulative returns relative to mean returns during the studied period for the five recommendation categories and for the various asset classes. Consistent with the former analyses, there is no clear association between relative cumulative returns and recommendations on the S&P 500 index, sector/industry/non-U.S. indices, bonds, and commodities. In contrast, both analyst groups are able to identify future trends in exchange rates.

[Please insert Figure 5 here]

The apparent success in predicting exchange rates should be interpreted with caution. For one, only 21 dual recommendations on exchange rates have been recorded. Moreover, the transparent monetary policies of central banks to keep interest rates low and improve liquidity could enhance the ability to predict future rates. Indeed, past work supports that hypothesis. For example, Szakmary and Mathur (1997) find that the profitability of technical rules in foreign exchange markets may be explained by a 'leaning against the wind' policy of central banks. LeBaron (1999) and Sapp (2004) report an association between technical rules and central banks interventions. Here we document the success of technical and fundamental analysts even when both schools of thought implement very different toolkits, which typically lead to very different predictions about the other asset classes.

The same line of reasoning, i.e., central bank firm intervention, does not apply to predicting prices of ten-year bonds, as prices of long term bonds may be exposed to other market factors beyond short-term interest rates. Indeed, ten-year risk-free rates exhibit considerable volatility during the sample period amounting to 6.66% in annual terms.

Table 5 reports summary statistics similar to those exhibited in Table 2 but focusing on all other asset classes. Staring with the market index, consistent with Figure 5a, there is no clear association between recommendations and subsequent returns. Null hypotheses that (i) the five recommendation categories have the same return distributions, (ii) returns corresponding to buy and strong buy fundamental recommendations and sell and strong sell fundamental recommendations have the same distribution, and (iii) the same as (ii) but for technical recommendations, are generally not rejected. When they are rejected, the difference goes in the wrong direction as mean returns corresponding to sell recommendations are higher than those corresponding to buy recommendations.

[Please insert Table 5 here]

Similar results are obtained for sector/industry/non-U.S. indices (Panel B), bonds (Panel C), and commodities (Panel D). Finally, the success of both fundamental and technical recommendations to predict exchange rates (Panel E) is statistically significant and robust. Here we display monotonically increasing average returns along the recommendation categories, for all investment horizons.

The apparent success to predict individual stock returns is the exception rather the rule. In all the other asset classes, excluding the U.S. dollar, both technicians and fundamentalists reveal no predictive ability. Our findings thus indicate that the markets corresponding to virtually all assets are efficient, yet inefficiency appears to exist among individual stocks.

5. Conclusion

This study employs a novel database from a leading media broadcast to confront head-to-head the performance of fundamental versus technical analysts and assess their real time economic value. The data is composed of dual fundamental and technical recommendations on the same underlying asset. The unique setup of the broadcast, featuring synchronized dual recommendations, multiple asset classes, and the presence of leading professionals, offers important insights in assessing the value of financial analysis. Ultimately, both fundamental and technical analysts are exposed to the same public information and their recommendations could differ due to distinct toolkits applied.

The simultaneous broadcast equates analyst exposure to herding, eliminates time gap biases such as cross-herding among analysts, and it allows one to control for the immediate short-term effect of the broadcast itself. The high profile of participating analysts levels the playing field thereby mitigating biases related to analysts' quality, experience, and career concerns. In addition, the broad focus of the program and the comprehensive list of assets covered make our findings general and mitigate concerns about illiquidity biases and exceptional observations.

Consistent with the semi-strong market efficiency hypothesis, the fundamental analysis reveals no ability, whatsoever, to predict future returns on all the assets examined. Surprisingly, technical analysts exhibit significant predicting ability of individual stock returns which could point to market inefficiency even among the universe of the largest and most traded stocks. For one, trading individual stocks based on technical recommendations yields large payoffs even after accounting for reasonable transaction costs. Moreover, such stock-picking ability is highly robust and is unaffected by controlling for common risk factors, firm's characteristics, including past returns, industry effects, analyst's gender, the potential immediate impact of the broadcast, transaction costs, and outliers.

However, the predicting ability of technicians characterizes individual stocks only. In contrast, returns on more general asset classes including equity indices, sectors, bonds, commodities, and market indexes, are unpredictable. Such differential results support the notion that the predictive ability of technical analysts relies on the possession of proprietary, publicly unknown, investment toolkits. Considering the nature of technical analysis, one appealing explanation is that such toolkits enable to extract private information from informed trading, which is more relevant to individual stocks and is virtually un-applicable to broader assets. Alternatively, technicians could process public information more effectively through their toolkits. In such case the success of technicians is more prominent in individual stocks as arbitrage capital is probably more invested in general assets and indexes thereby eliminating abnormal profits in those assets.

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Table 1: Overview of recommendation categories for various asset classes

The table displays the frequency of recommendation categories for various asset classes. The sample period is November 8, 2011 (the day when a first simultaneous fundamental-technical comparison was broadcasted) through December, 31 2014. The Spearman's correlation coefficient is between the numerical values of fundamental and technical recommendations (e.g., strong sell=1). The Pearson's Chi-square null hypothesis asserts that frequencies of fundamental and technical recommendations across categories are not significantly different.

	Technical \ Fundamental	Strong Sell	Sell	Hold	Buy	Strong buy	Total	Spearman's correlation	Pearson's Chi-Square
262 stocks (159 fundamental analysts–17 females; 34 technical analysts –3 females)	Strong Sell	12	24	10	19	7	**72**		
	Sell	9	85	44	103	22	**263**		
	Hold	8	35	31	77	23	**174**		
	Buy	23	106	71	111	29	**340**		
	Strong buy	12	38	23	34	44	**151**		4.15
	Total	**64**	**288**	**179**	**344**	**125**	**1000**	0.05	(*p*=0.39)
The U.S. market (S&P 500) (24 fundamental analysts–4 females; 22 technical analysts–3 females)	Strong Sell	0	2	0	0	0	**2**		
	Sell	0	14	10	12	1	**37**		
	Hold	1	10	8	9	0	**28**		
	Buy	1	18	17	33	2	**71**		
	Strong buy	0	2	4	3	2	**11**		6.63
	Total	**2**	**46**	**39**	**57**	**5**	**149**	0.18	(*p*=0.16)
58 sector / industry / non-U.S. index (34 fundamental analysts–4 females; 28 technical analysts–3 females)	Strong Sell	4	12	4	4	1	**25**		
	Sell	4	31	19	15	5	**74**		
	Hold	1	18	20	13	2	**54**		
	Buy	2	28	22	32	1	**85**		
	Strong buy	0	3	7	3	5	**18**		12.77
	Total	**11**	**92**	**72**	**67**	**14**	**256**	0.21	(*p*=0.01)
3 bond types (14 fundamental analysts–3 females; 13 technical analysts–2 females)	Strong Sell	0	1	0	1	0	**2**		
	Sell	1	5	3	3	0	**12**		
	Hold	0	5	5	3	0	**13**		
	Buy	0	7	4	6	0	**17**		
	Strong buy	0	1	0	2	3	**6**		3.12
	Total	**1**	**19**	**12**	**15**	**3**	**50**	0.29	(*p*=0.54)
17 commodities (31 fundamental analysts –3 females; 20 technical analysts–3 females)	Strong Sell	12	13	3	5	0	**33**		
	Sell	5	31	6	11	2	**55**		
	Hold	2	11	5	4	0	**22**		
	Buy	1	7	7	12	0	**27**		
	Strong buy	0	1	3	0	3	**7**		4.61
	Total	**20**	**63**	**24**	**32**	**5**	**144**	0.38	(*p*=0.33)
4 exchange rates (9 fundamental analysts–3 females; 9 technical analysts–1 female)	Strong Sell	0	1	0	0	0	**1**		
	Sell	0	3	1	0	0	**4**		
	Hold	0	1	0	2	0	**3**		
	Buy	1	1	2	7	1	**12**		
	Strong buy	0	0	0	0	1	**1**		1.17
	Total	**1**	**6**	**3**	**9**	**2**	**21**	0.51	(*p*=0.88)

Table 2: Stock returns per recommendation category

The table describes the relation between return and the recommendation category. Investment horizons are one, three, six, and nine months following the recommendations. Panel A (B) considers raw (risk-adjusted) average returns, with risk adjustment pertaining to the Fama and French and momentum factors. All sell (buy) recommendations encompass both sell and strong sell (buy and strong buy) recommendations. The Kruskal-Wallis null hypothesis asserts that the five categories deliver the same return distribution. The Mann-Whitney null hypothesis asserts that all buy and all sell recommendations exhibit the same return distribution.

	Fundamental recommendations									Technical recommendations								
	Strong. Sell	**Sell**	**Hold**	**Buy**	**Strong. buy**	**Kruskal -Wallis**	**All sell**	**All buy**	**Mann-Whitney**	**Strong. sell**	**Sell**	**Hold**	**Buy**	**Strong. Buy**	**Kruskal -Wallis**	**All sell**	**All buy**	**Mann-Whitney**
									A. Raw returns									
One month																		
Mean	1.3	1.2	1.5	0.8	2.6		1.2	1.3		-1.1	0.2	2.4	2.0	1.7		0.0	1.9	
Std. dev.	17.3	11.4	9.8	9.4	10.4		12.7	9.7		12.0	10.0	12.4	10.0	11.4		10.4	10.4	
Skewness	1.9	1.4	2.3	-0.4	1.0		1.6	0.1		0.1	-0.4	1.1	2.1	2.8		-0.3	2.4	
Max	87.0	91.1	71.8	37.1	57.3	2.56	91.1	57.3	0.45	41.8	37.1	71.8	87.0	91.1	**11.18**	41.8	91.1	**2.60**
Min	-33.9	-39.0	-27.1	-54.7	-30.0	(0.63)	-39.0	-54.7	(0.325)	-38.3	-54.7	-33.9	-27.1	-36.0	**(0.02)**	-54.7	-36.0	**(0.01)**
Three months																		
Mean	3.6	4.2	6.4	4.4	8.6		4.1	5.5		0.3	4.4	6.3	5.6	6.6		3.5	5.9	
Std. dev.	24.1	18.3	19.1	14.6	17.9		19.5	15.6		21.3	19.1	17.9	16.0	16.5		19.7	16.1	
Skewness	1.0	0.6	1.2	0.1	1.1		0.8	0.6		-0.1	1.0	1.1	1.1	0.6		0.7	0.9	
Max	109.9	102.0	88.7	55.1	92.5	7.08	109.9	92.5	1.22	51.4	102.0	92.5	109.9	76.1	8.13	102.0	109.9	**2.33**
Min	-46.0	-64.4	-39.5	-63.8	-46.3	(0.13)	-64.4	-63.8	(0.11)	-64.4	-63.8	-40.9	-39.9	-46.3	(0.09)	-64.4	-46.3	**(0.01)**
Six months																		
Mean	8.3	10.6	10.5	8.6	16.1		10.2	10.6		3.6	7.2	11.8	10.8	16.8		6.5	12.7	
Std. dev.	34.9	26.3	25.7	21.6	27.1		28.0	23.4		27.0	24.7	30.1	22.2	25.9		25.2	23.6	
Skewness	0.9	1.4	2.3	0.5	3.2		1.2	1.7		1.1	1.0	3.2	0.7	1.5		1.0	1.0	
Max	134.0	166.8	199.4	119.1	216.0	**10.35**	166.8	216.0	1.10	119.1	130.6	216.0	134.0	166.8	**27.19**	130.6	166.8	**4.46**
Min	-54.2	-77.1	-53.6	-51.8	-53.1	**(0.04)**	-77.1	-53.1	(0.14)	-53.6	-51.8	-54.2	-77.1	-57.9	**(0.00)**	-53.6	-77.1	**(0.00)**
Nine months																		
Mean	10.3	18.4	19.6	13.8	21.5		16.9	15.8		11.2	13.8	16.9	17.0	24.8		13.3	19.4	
Std. dev.	48.5	36.1	36.0	29.2	34.2		38.8	30.8		41.7	34.3	37.6	29.7	37.1		36.0	32.4	
Skewness	1.8	2.2	2.5	1.1	1.9		2.0	1.4		1.6	2.0	2.5	1.6	1.9		1.8	1.8	
Max	238.8	242.4	258.8	199.2	217.9	9.58	242.4	217.9	0.58	199.2	242.4	258.8	238.8	236.3	**15.62**	242.4	238.8	**3.41**
Min	-55.5	-54.3	-58.6	-58.7	-68.7	(0.05)	16.9	15.8	(0.21)	-68.7	-58.7	-55.9	-58.6	-40.3	**(0.00)**	-68.7	-58.6	**(0.00)**
									B. Risk adjusted returns									
One month																		
Mean	-0.6	-0.3	0.4	-0.5	0.6		-0.4	-0.2		-3.0	-1.1	0.2	0.9	0.2		-1.5	0.6	
Std. dev.	16.2	10.5	8.4	8.0	9.5		11.8	8.4		11.1	8.9	10.9	8.8	10.7		9.4	9.4	
Skewness	1.6	1.8	1.6	-0.4	0.9		1.8	0.1		-0.2	-0.3	0.7	2.2	3.5		-0.3	2.8	
Max	74.6	90.6	50.1	29.3	52.2	2.73	90.6	52.2	73	34.1	31.7	52.2	74.6	90.6	**14.87**	34.1	90.6	**3.34**
Min	-35.5	-40.6	-24.7	-46.9	-31.5	(0.60)	-40.6	-46.9	(0.23)	-40.6	-46.9	-35.5	-24.7	-38.3	**(0.01)**	-46.9	-38.3	**(0.00)**
Three months																		
Mean	-1.1	-0.6	2.1	0.0	2.5		-0.7	0.7		-4.9	-0.4	1.8	1.1	1.4		-1.4	1.2	
Std. dev.	21.5	16.9	16.5	13.0	15.6		17.8	13.8		19.2	17.1	15.8	14.2	14.8		17.6	14.4	
Skewness	1.1	0.5	1.0	0.3	0.9		0.7	0.6		0.1	1.0	1.2	0.7	0.5		0.7	0.6	
Max	92.2	82.1	74.2	59.7	73.6	5.91	92.2	73.6	1.21	44.4	82.1	73.6	92.2	64.3	**12.87**	82.1	92.2	**3.00**
Min	-41.3	-62.3	-38.0	-59.7	-50.1	(0.21)	-62.3	-59.7	(0.11)	-62.3	-59.7	-34.1	-41.3	-50.1	**(0.01)**	-62.3	-50.1	**(0.00)**
Six months																		
Mean	-1.3	0.7	2.1	-0.3	5.0		0.4	1.1		-5.2	-1.8	2.6	1.8	5.5		-2.5	2.9	
Std. dev.	30.8	23.0	22.4	18.2	22.6		24.6	19.6		23.1	21.2	25.5	19.6	22.3		21.6	20.5	
Skewness	0.9	1.3	1.8	0.1	3.0		1.1	1.4		0.6	0.7	2.8	0.6	1.5		0.7	1.0	
Max	110.5	143.0	155.4	76.2	170.1	7.91	143.0	170.1	1.21	76.2	104.1	170.1	110.5	143.0	**23.21**	104.1	143.0	**4.25**
Min	-54.9	-76.2	-57.5	-55.9	-56.9	(0.10)	-76.2	-56.9	(0.11)	-57.5	-55.9	-54.9	-76.2	-61.4	**(0.00)**	-57.5	-76.2	**(0.00)**
Nine months																		
Mean	-4.1	2.8	4.5	0.3	4.6		1.5	1.4		-3.5	-0.6	2.7	2.5	7.4		-1.2	4.0	
Std. dev.	39.1	28.6	28.2	23.6	26.0		30.8	24.4		33.0	27.1	29.7	23.8	29.0		28.5	25.7	
Skewness	1.6	2.1	1.7	0.7	1.6		1.8	1.0		1.4	1.6	1.7	1.3	1.9		1.5	1.6	
Max	172.0	182.5	160.0	135.1	152.3	8.64	182.5	152.3	1.03	135.1	170.9	160.0	172.0	182.5	**17.22**	170.9	182.5	**3.74**
Min	-61.6	-57.9	-52.6	-64.3	-71.9	(0.07)	-61.6	-71.9	(0.15)	-71.9	-64.3	-61.6	-57.9	-52.4	**(0.00)**	-71.9	-57.9	**(0.00)**

Table 3: Stock recommendations: cross-section regressions

The table reports the results of the cross section regression

$$R_i = \gamma_0 + \gamma_1 REC_i + \gamma_2 ME_i + \gamma_3 (BE_i / ME_i) + \gamma_4 VOL_i + \gamma_5 VOLUME_i + \sum_{j=1}^{3} \gamma_{6j} R_i^j + \gamma_7 \Delta VOLUME_i + \gamma_8 \Delta VOL_i + \sum_{j=1}^{2} \gamma_{9j} RECIMPACT_i^j + \sum_{j=1}^{2} \gamma_{10j} SURPRISE_i^j + \varepsilon_i,$$

where i is the stock-specific subscript, R_i is the investment return; REC_i describes the recommendation category (1-strong sell, 5-strong buy); ME_i is the previous year log of the market capitalization; BE_i is the previous year positive book value and zero otherwise; VOL_i is return volatility measured from daily returns over the year prior to the recommendation broadcast; $VOLUME_i$ is the log of the average daily trading volume over the year prior to the recommendation broadcast; $R_i^{j=1,2,3}$ denote returns during six months, one month, and two through four months prior to the recommendation broadcast; ΔVOL_i and $\Delta VOLUME_i$ are, respectively, the changes in volatility and volume during the last three months prior to the recommendation broadcast relative to previous year figures; $RECIMPACT_i^{j=1,2}$ are the return and change in volume over three days following the recommendation broadcast, intended to control for any immediate impact of recommendations; and $SURPRISE_i^{j=1,2}$ are the percentage surprises in earning per share during the past two quarters.

The first line in each test reports the coefficient value, while the second line reports the *t*-value (in brackets) corresponding to heteroskedasticity- and autocorrelation-consistent (HAC) standard errors sorted on analysts. One and two asterisks indicate a significance level of 5% and 1%, respectively.

			Recommendation		Firm characteristics				Potential explanation									
Dependent									Past return			ΔVolume	ΔVolatility	Rec. impact		Surprise		
variable	Test	Const.	Fundamental	Technical	ME	BE/ME	Volatility	Volume	6m	1m	2–4m	3m	3m	Return	ΔVolume	3m	6m	*F*
	1a.	0.081	0.007															1.13
		(2.72^{**})	(1.06)															
	1b.	0.017		0.027														46.2
		(1.11)		(6.80^{**})														
	2a.	0.077	0.006						0.053									2.6
		(2.90^{**})	(0.89)						(1.72)									
	2b.	0.019		0.024					0.044									18.9
Six months		(1.08)		(5.48^{**})					(2.41^{*})									
returns	3a.	-0.008	0.0089		-0.005	-0.000	1.173	0.007	0.038									5.3
		(-0.07)	(1.17)		(-0.43)	(-1.45)	(0.63)	(0.76)	(1.21)									
	3b	-0.039		0.024	-0.005	-0.000	1.142	0.005	0.030									16.8
		(-0.29)		(5.51^{**})	(-0.46)	(-1.50)	(0.85)	(0.61)	(1.23)									
	4a.	0.142	0.004		-0.004	-0.000	2.489	-0.003	0.007	-0.036	0.045	0.043	0.019	0.955	-0.081	0.010	-0.022	14.1
		(1.23)	(0.59)		(-0.36)	(-1.82)	(1.22)	(-0.29)	(0.15)	(-0.34)	(0.59)	(0.91)	(0.39)	(4.76^{**})	(-3.83^{**})	(0.83)	(-1.73)	
	4b.	0.103		0.020	-0.003	-0.000	2.577	-0.004	0.007	-0.069	0.035	0.040	0.029	0.944	-0.077	0.010	-0.022	30.6
		(0.74)		(3.48^{**})	(-0.36)	(-2.00^{*})	(1.68)	(-0.46)	(0.20)	(-0.63)	(0.45)	(0.86)	(0.40)	(5.34^{**})	(-2.89^{**})	(0.93)	(-1.67)	
	5a.	-0.033	0.007		-0.006	-0.000	0.292	0.004	0.025									10.0
		(-0.32)	(1.14)		(-0.54)	(-1.97^{*})	(0.18)	(0.51)	(0.97)									
Six months	5b.	-0.060		0.021	-0.005	-0.000	0.269	0.003	0.018									50.2
returns		(-0.43)		(5.67^{**})	(-0.64)	(-2.08^{*})	(0.23)	(0.34)	(0.93)									
adjusted to	6a.	0.086	0.0034		-0.003	-0.000	2.324	-0.005	-0.017	-0.026	0.063	0.049	0.027	0.778	-0.073	0.010	-0.018	24.5
four factors		(0.80)	(0.57)		(-0.30)	(-1.74)	(1.21)	(-0.59)	(-0.43)	(-0.30)	(0.87)	(1.09)	(0.61)	(4.08^{**})	(-4.40^{**})	(1.05)	(-1.81)	
	6b.	0.052		0.017	-0.003	-0.000	1.921	-0.006	-0.017	-0.055	0.054	0.047	0.036	0.768	-0.069	0.011	-0.018	24.2
		(0.36)		(3.52^{**})	(-0.30)	(-2.22^{*})	(1.35)	(-0.70)	(-0.48)	(-0.56)	(0.66)	(1.14)	(0.55)	(4.96^{**})	(-3.20^{**})	(1.18)	(-1.78)	

Dependent variable		Const.	Recommendation: Fundamental		Recommendation: Technical		Firm characteristics: ME	BE/ME	Volatility	Volume	Past return 6m	*F* for gender	*F*
			Male	Female	Male	Female							
6 months returns	7a.	-0.001	0.010	0.004			-0.005	-0.000	1.137	0.006	0.038	1.93	4.7
		(-0.01)	(1.35)	(0.50)			(-0.43)	(-1.46)	(0.61)	(0.72)	(1.22)	(*p* = 0.17)	
	7b.	-0.037			0.024	0.029	-0.004	-0.000	1.111	0.005	0.030	0.25	14.5
		(-0.28)			(5.10**)	(3.47**)	(-0.45)	(-1.51)	(0.79)	(0.80)	(1.23)	(*p* = 0.62)	
1 month returns	8a.	0.017	0.001				-0.005	-0.000	-0.127	0.003	0.006		1.1
		(0.58)	(0.49)				(-1.65)	(-0.36)	(-0.24)	(1.06)	(0.55)		
	8b.	0.007			0.007		-0.005	-0.000	-0.121	0.002	0.004		5.7
		(0.21)			(2.40*)		(-1.48)	(-0.28)	(-0.29)	(1.00)	(0.32)		
3 months returns	9a.	0.045	0.007				-0.010	-0.000	-0.166	0.006	0.005		0.8
		(0.55)	(1.009)				(-1.43)	(-1.66)	(-0.15)	(0.99)	(0.20)		
	9b.	0.045			0.009		-0.010	-0.000	-0.246	0.006	0.002		3.4
		(0.56)			(2.23*)		(-1.72)	(-1.37)	(-0.26)	(1.23)	(0.19)		
9 months returns[a]	10a.	-0.054	0.010				0.012	-0.000	5.533	-0.003	0.021		8.0
		(-0.39)	(0.98)				1.03	(-0.11)	(2.93**)	(-0.30)	(0.43)		
	10b.	-0.082			0.025		0.012	0.000	5.490	-0.005	0.012		17.2
		(-0.47)			(3.29**)		(1.01)	(0.12)	(3.46**)	(-0.42)	(0.30)		
6 months returns, 4 categories (no hold)	11a.	-0.007	0.008				0.001	-.000	1.169	0.003	0.0345		1.3
		(-0.06)	(1.08)				(0.07)	(-0.45)	(0.57)	(0.32)	(0.92)		
	11b.	-0.023			0.025		-0.006	-0.000	0.154	0.006	0.043		11.1
		(-0.16)			(5.71**)		(-0.74)	(-1.15)	(0.16)	(0.74)	(2.20*)		
6 months returns, 2 categories (buy, sell)	12a.	0.006	0.004				0.001	-0.000	1.0058	0.003	0.036		1.1
		(0.06)	(0.24)				(0.11)	(-0.32)	(0.52)	(0.33)	(0.96)		
	12b.	-0.036			0.054		-0.006	-0.000	0.106	0.006	0.045		9.4
		(-0.23)			(4.12**)		(-0.75)	(-1.16)	(0.11)	(0.79)	(2.32*)		
6 months returns, Winsorising at 2.5%	13a.	-0.017	0.007				-0.003	-0.000	0.122	0.007	0.053		7.9
		(-0.17)	(1.34)				(-0.33)	(-1.60)	(0.10)	(0.92)	(1.94)		
	13b.	-0.050			0.024		-0.003	-0.000	0.112	0.006	0.044		27.1
		(-0.39)			(5.88**)		(-0.41)	(-1.97*)	(0.13)	(0.76)	(2.39*)		
6 months returns, Quantile regression (τ=0.5)	14a.	-0.174	0.010				-0.013	-0.000	-1.886	0.024	0.076		
		(-2.18*)	(1.81)				(-1.60)	(-0.14)	(-1.37)	(3.81**)	(6.16**)		
	14b.	-0.127			0.018		-0.009	-0.000	-1.761	0.018	0.062		
		(-1.57)			(3.45**)		(-1.21)	(-0.11)	(-1.32)	(2.91**)	(4.05**)		
6 months returns , including single recommendations (no comparison)	15a.	-0.052	0.012				-0.004	0.000	0.993	0.008	0.044		6.9
		(-0.50)	(1.57)				(-0.31)	(-1.30)	(0.54)	(0.97)	(1.44)		
	15b.	-0.050			0.023		-0.006	-0.000	1.199	0.007	0.024		12.4
		(-0.37)			(5.99**)		(-0.64)	(-0.72)	(0.89)	(0.82)	(0.97)		

[a] The nine-month's results are subject to updates based on future returns.

Table 4. Industry and style effects

The table reports the results of the regression:

$$R_i = \gamma_0 + \sum_j \gamma_{1j}(REC_i)(FIRM_{ij}) + \varepsilon_i,$$

where R is stock return or return adjusted for Fama-French and momentum factors (R_{adj}) over six months following the recommendation broadcast; REC_i describes the recommendation category (1-strong sell, 5-strong buy); $FIRM_{ij}$ are firm characteristics' dummies: Seven industry dummies in Panel A and three dummies in Panel B corresponding to bottom 30%, core 40%, and top 30% of either firm's size, the book-to-market ratio, volatility, and past return from two to 12 months prior to recommendation broadcast.

The first line in each test reports the coefficient value, while the second line reports the t-value (in brackets) corresponding to heteroskedasticity- and autocorrelation-consistent (HAC) standard errors sorted on analysts. One and two asterisks indicate a significance level of 5% and 1%, respectively.

A. Industry

Recommendations		Constant	Mining	Manufacturing & Construction	Transportation & Public utilities	Wholesale & Retail trade	Finance, Insurance, Real estate & Public administration	Services	F all industries equal (p-value)
Number of observations			15	382	67	238	71	227	
Fundamental	R	0.082	-0.037	0.008	0.013	-0.003	0.008	0.016	6.6
		(2.90**)	(-3.60**)	(0.90)	(1.64)	(-0.31)	(0.99)	(2.48*)	($p < 0.001$)
	R_{adj}	-0.011	-0.027	0.007	0.011	0.001	0.001	0.014	3.8
		(-0.47)	(-2.37*)	(0.98)	(1.53)	(0.18)	(0.13)	(2.21*)	($p = 0.002$)
Technical	R	0.017	-0.022	0.027	0.030	0.016	0.026	0.041	12.1
		(0.94)	(-1.40)	(4.97**)	(5.91**)	(1.96)	(3.66**)	(5.24**)	($p < 0.001$)
	R_{adj}	-0.064	-0.015	0.023	0.023	0.016	0.016	0.035	7.3
		(-4.61**)	(-0.92)	(5.20**)	(5.20**)	(2.63**)	(2.63**)	(5.21**)	($p < 0.001$)

B. Firm's attributes

Firm's variable:	**Size**				**BE/ME**				**Volatility**				**Past return**			
Recommendations:	**Fundamental**		**Technical**		**Fundamental**		**Technical**		**Fundamental**		**Technical**		**Fundamental**		**Technical**	
Return type:	R	R_{adj}	R	R_{adj}	R	R_{adj}	R	R_{adj}	R	R_{adj}	R	R_{adj}	R	R_{adj}	R	R_{adj}
Constant	0.080	-0.013	0.017	-0.063	0.018	-0.009	0.017	-0.063	0.090	-0.001	0.018	-0.062	0.091	-0.002	0.020	-0.060
	(2.63**)	(-0.53)	(1.10)	(-5.10**)	(0.78)	(-0.37)	(1.07)	(-5.30**)	(3.31**)	(-0.03)	(0.98)	(-4.51**)	(2.99**)	(-0.10)	(1.08)	(-4.26**)
Bottom					0.010	0.010	0.032	0.027	0.001	-0.004	0.029	0.020	0.013	0.011	0.035	0.030
					(1.45)	(1.52)	(7.03**)	(6.95**)	(0.10)	(-0.40)	(4.04**)	(3.56**)	(1.11)	(1.15)	(7.39**)	(7.63**)
Core	0.020	0.017	0.046	0.037	-0.001	0.001	0.020	0.017	0.016	0.012	0.035	0.028	0.006	0.006	0.028	0.023
	(2.38*)	(2.35*)	(5.86**)	(5.57**)	(-0.09)	(0.13)	(3.59**)	(4.49**)	(2.15*)	(1.92)	(5.82**)	(5.46**)	(1.03)	(1.28)	(5.98**)	(6.22**)
Top	0.005	0.005	0.023	0.019	-0.001	-0.003	0.019	0.012	-0.003	-0.001	0.019	0.019	-0.001	-0.001	0.021	0.017
	(0.68)	(0.78)	(4.99**)	(4.93**)	(-0.10)	(-0.37)	(3.22**)	(2.92**)	(-0.50)	(-0.09)	(3.65**)	(4.93**)	(-0.08)	(-0.11)	(2.96**)	(3.02**)
F all equal					3.02	3.01	6.44	5.20	12.67	9.18	28.87	3.81	2.38	2.34	2.15	2.51
(p-value)					(0.05)	(0.05)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.09)	(0.10)	(0.12)	(0.08)
F bottom equal top	2.21	2.272	5.26	4.88	3.87	5.23	2.62	6.82	0.16	0.15	2.46	0.09	2.08	2.44	3.76	4.87
(p-value)	(0.14)	(0.13)	(0.02)	(0.03)	(0.05)	(0.02)	(0.11)	(0.01)	(0.69)	(0.70)	(0.12)	(0.76)	(0.15)	(0.10)	(0.05)	(0.03)

Table 5. Summary statistics of average returns on various asset classes

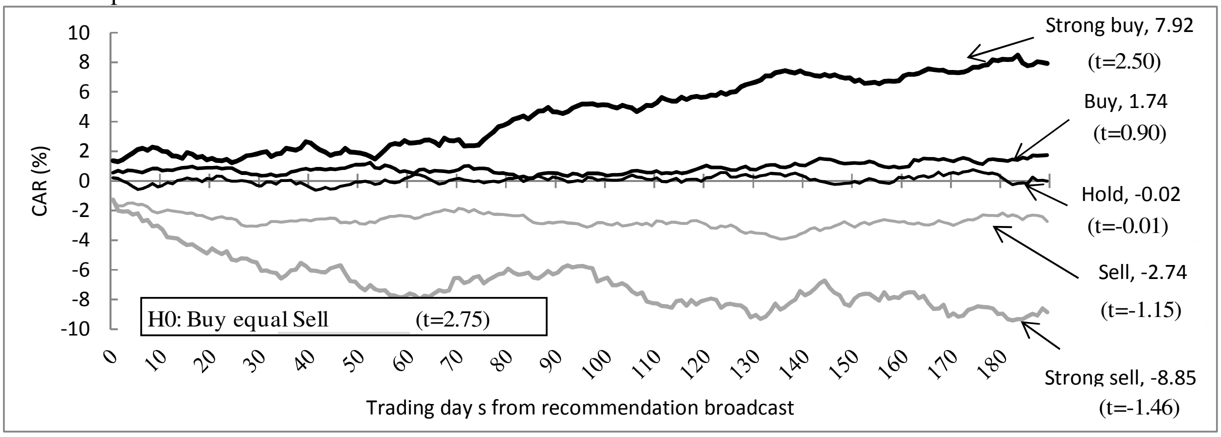
The table reports summary statistics of returns on various asset classes for each recommendation category over one, three, six, and nine months following the recommendations broadcast. Asset classes are the S&P500 index, sector/industry/non-U.S. stock indices, U.S. bonds, commodities, and the U.S. dollar. The Kruskal-Wallis test null hypothesis asserts that investment returns based on the five categories have the same distribution. The Mann-Whitney null hypothesis asserts that all buy and all sell recommendations have the same distribution. When no statistic exists it is denoted "not applicable" (na).

		Fundamental recommendations							Technical recommendations						
		Strong sell	Sell	Hold	Buy	Strong buy	Kruskal-Wallis	Mann-Whitney	Strong sell	Sell	Hold	Buy	Strong buy	Kruskal-Wallis	Mann-Whitney
		A. Underlying asset is the U.S. market (S&P 500 index)													
One month	Mean	3.9	2.2	1.0	1.6	2.4			3.9	2.1	2.5	1.2	1.1		
	Std. dev.	1.8	2.4	3.3	2.7	1.7			1.5	2.9	3.0	2.5	3.0		
	Skewness	na	0.5	-0.4	0.1	0.5			na	-0.5	-0.6	0.0	0.3		
	Max	5.6	8.9	7.8	7.9	4.8	5.25	1.48	5.4	8.9	7.9	8.9	6.7	9.11	2.20
	Min	2.1	-2.4	-6.7	-5.6	0.6	(0.26)	(0.07)	2.4	-6.7	-6.5	-5.6	-3.9	(0.06)	(0.01)
Three months	Mean	7.6	4.1	4.8	4.3	4.0			4.5	4.3	5.0	4.2	4.9		
	Std. dev.	1.5	3.6	2.4	3.5	3.1			1.4	3.6	3.3	3.2	2.7		
	Skewness	na	0.1	-0.4	1.1	0.6			na	0.7	-0.9	0.8	1.0		
	Max	9.2	14.7	10.4	15.8	9.0	5.65	0.61	5.9	14.7	10.4	15.8	10.7	3.52	0.06
	Min	6.1	-4.7	-1.3	-1.4	0.1	(0.23)	(0.27)	3.0	-1.4	-4.7	-3.0	1.4	(0.48)	(0.48)
Six months	Mean	13.9	8.2	7.7	7.5	7.6			11.4	8.3	8.0	7.5	8.0		
	Std. dev.	1.7	2.9	3.3	3.1	2.6			4.4	2.9	2.9	3.3	2.7		
	Skewness	na	0.4	0.8	0.3	1.5			na	0.7	-0.7	0.8	0.6		
	Max	15.6	15.9	18.4	15.8	12.5	6.23	1.57	15.9	15.8	12.5	18.4	12.5	3.56	1.43
	Min	12.2	3.3	1.6	2.2	4.8	(0.18)	(0.06)	7.0	2.8	1.6	2.2	4.5	(0.47)	(0.08)
Nine months[a]	Mean	16.3	10.9	11.4	12.2	12.3			13.2	11.1	12.1	11.4	13.1		
	Std. dev.	1.1	4.0	4.1	4.7	2.7			4.3	4.5	3.3	4.6	3.9		
	Skewness	na	0.9	0.4	0.4	1.6			na	1.1	-0.1	0.5	0.5		
	Max	17.4	21.5	22.5	22.6	16.7	4.99	1.19	17.5	22.6	17.6	22.2	20.9	3.92	0.76
	Min	15.2	5.6	3.8	3.8	10.0	(0.29)	(0.12)	8.9	5.6	6.2	3.8	7.1	(0.42)	(0.22)
		B. Underlying asset is sector/industry/non-U.S. indices													
One month	Mean	3.1	0.8	1.6	1.6	1.6			1.7	1.3	1.6	1.3	0.7		
	Std. dev.	4.4	5.8	3.9	4.4	4.8			4.3	4.9	5.0	5.1	3.8		
	Skewness	0.9	-0.7	-0.6	-0.6	-0.3			0.5	-1.0	0.1	-1.2	-0.4		
	Max	11.4	17.6	12.5	11.3	10.1	1.51	0.58	15.3	11.4	17.6	13.2	7.1	0.69	0.48
	Min	-2.4	-21.6	-12.1	-14.3	-9.5	(0.83)	(0.28)	-9.1	-15.0	-12.8	-21.6	-8.2	(0.95)	(0.32)
Three months	Mean	5.9	3.1	4.4	4.2	2.9			3.4	5.0	4.1	3.4	1.6		
	Std. dev.	9.2	8.6	6.1	8.2	4.8			7.3	6.9	8.8	7.5	8.3		
	Skewness	0.9	-1.0	0.0	-0.5	0.2			0.9	-0.2	-0.7	-1.0	-1.2		
	Max	27.9	26.6	22.8	27.1	12.6	2.26	0.55	25.4	27.9	27.1	19.4	16.8	4.44	1.30
	Min	-8.0	-33.4	-13.2	-23.2	-5.9	(0.69)	(0.29)	-8.0	-21.7	-33.4	-26.7	-23.2	(0.35)	(0.01)
Six months	Mean	9.7	5.2	6.1	4.6	5.0			6.6	5.8	6.2	4.4	5.4		
	Std. dev.	7.3	10.8	9.0	10.9	7.5			10.1	9.1	9.6	11.0	10.7		
	Skewness	1.1	-1.0	0.0	-0.8	1.4			-1.3	-0.9	0.3	-1.2	0.5		
	Max	25.5	29.9	35.5	30.6	26.2	2.11	0.88	29.9	26.2	35.5	30.6	33.6	1.37	1.05
	Min	2.3	-35.7	-23.1	-29.1	-5.4	(0.72)	(0.19)	-29.0	-20.8	-23.3	-35.7	-17.2	(0.85)	(0.15)
Nine months[a]	Mean	13.6	8.3	11.5	10.5	9.7			10.2	8.9	11.6	10.2	9.6		
	Std. dev.	8.3	12.8	10.6	15.2	11.0			12.7	11.5	12.3	13.8	13.6		
	Skewness	1.2	-1.1	0.6	-0.8	0.8			-2.1	-0.9	0.8	-0.9	-0.6		
	Max	32.2	45.7	50.9	51.8	37.3	2.30	0.71	33.0	37.3	51.8	45.7	40.1	0.53	0.45
	Min	5.5	-38.3	-18.0	-34.8	-7.4	(0.68)	(0.24)	-38.3	-31.0	-23.6	-36.9	-26.3	(0.97)	(0.33)
		C. Underlying asset is bonds													
One month	Mean	1.2	0.6	0.5	-0.5	-0.6			-1.0	0.8	0.8	-0.5	0.1		
	Std. dev.	0.0	1.3	1.4	2.5	1.5			2.4	1.6	1.4	2.1	1.3		
	Skewness	na	0.6	-0.5	-0.6	1.0			na	0.0	-0.4	-1.0	-0.9		
	Max	1.2	3.9	2.6	3.4	1.4	2.58	1.52	1.4	3.9	3.4	2.6	1.4	4.76	1.44
	Min	1.2	-1.8	-1.7	-6.2	-2.1	(0.63)	(0.06)	-3.4	-1.6	-2.4	-6.2	-2.1	(0.31)	(0.08)

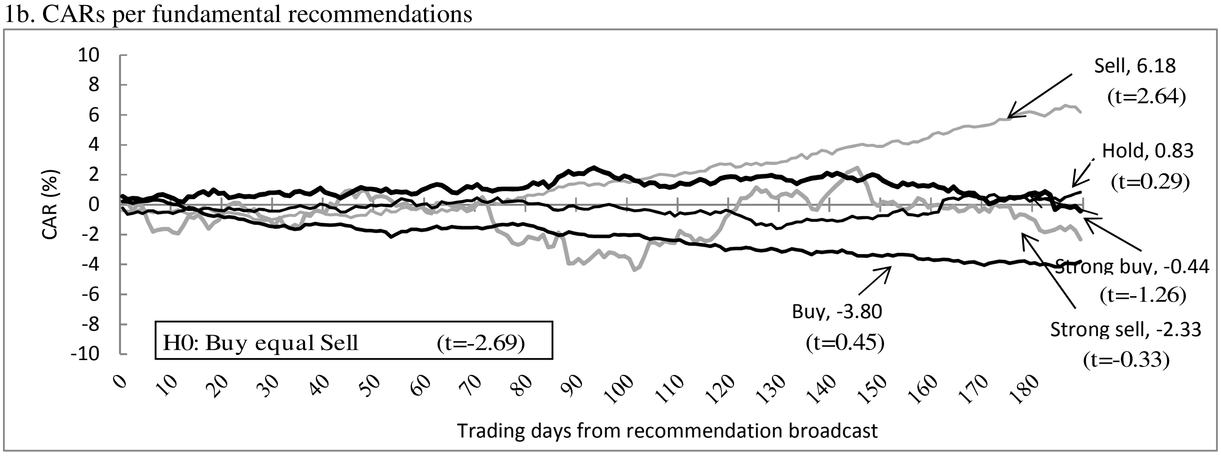
		Fundamental recommendations							Technical recommendations						
		Strong sell	Sell	Hold	Buy	Strong buy	Kruskal-Wallis	Mann-Whitney	Strong sell	Sell	Hold	Buy	Strong buy	Kruskal-Wallis	Mann-Whitney
Three months	Mean	2.3	0.9	1.8	-0.5	-0.2			0.2	1.6	2.0	-0.8	0.3		
	Std. dev.	0.0	2.4	1.1	2.9	1.3			0.7	1.2	1.7	3.1	1.1		
	Skewness	na	-0.3	0.2	-1.8	-1.4			na	-0.6	1.1	-1.1	-1.4		
	Max	2.3	6.2	3.9	2.6	1.0	9.27	**2.02**	0.9	3.6	6.2	2.9	1.4	**12.15**	**2.38**
	Min	2.3	-3.9	0.2	-8.4	-1.9	(0.06)	**(0.02)**	-0.5	-0.7	-0.1	-8.4	-1.9	**(0.02)**	**(0.01)**
Six months	Mean	6.3	2.2	2.9	0.6	-0.2			0.7	3.5	2.6	0.6	0.5		
	Std. dev.	0.0	2.8	2.0	4.0	2.1			2.2	3.0	2.4	3.5	2.6		
	Skewness	na	-0.1	-1.2	-0.3	-1.7			na	0.3	-1.2	-1.0	-0.5		
	Max	6.3	8.6	5.5	8.3	1.5	8.68	**1.81**	2.9	8.6	5.2	5.2	3.9	5.58	1.63
	Min	6.3	-3.2	-2.3	-7.5	-3.2	(0.07)	**(0.04)**	-1.5	-1.3	-3.2	-7.5	-3.2	(0.63)	(0.05)
Nine months[a]	Mean	5.6	2.5	3.2	2.4	2.5			3.0	3.9	2.5	1.5	4.2		
	Std. dev.	0.0	4.0	3.0	4.2	2.5			3.3	1.4	2.6	5.2	3.0		
	Skewness	na	-0.8	0.3	-0.8	-1.1			na	-1.0	1.6	-0.3	-0.7		
	Max	5.6	9.7	9.2	9.6	5.1	1.47	0.07	6.2	5.7	9.2	9.7	8.4	3.74	0.94
	Min	5.6	-8.9	-2.0	-6.2	-0.9	(0.83)	(0.47)	-0.3	0.4	-0.6	-8.9	-0.9	(0.44)	(0.17)
D. Underlying asset is commodities															
One month	Mean	0.0	-2.0	-4.5	-2.3	-0.8			-2.9	-1.5	-2.2	-2.4	-3.2		
	Std. dev.	4.7	7.2	9.1	6.6	5.3			6.0	8.8	6.8	5.8	3.0		
	Skewness	-1.4	-0.2	-0.7	0.0	-0.3			-0.9	-0.7	-1.2	0.6	-1.3		
	Max	6.0	19.5	14.3	10.0	7.0	5.75	0.64	6.9	19.5	10.3	14.3	0.0	2.72	0.98
	Min	-14.6	-23.7	-26.5	-16.8	-9.4	(0.22)	(0.26)	-20.6	-26.5	-22.9	-11.8	-9.4	(0.61)	(0.16)
Three months	Mean	-3.4	-4.9	-6.6	-1.6	-7.6			-6.1	-3.8	-1.6	-4.8	-7.0		
	Std. dev.	11.3	13.5	11.3	9.4	8.1			15.1	12.2	10.6	8.5	6.1		
	Skewness	-1.9	-1.5	-0.6	-1.3	-0.2			-1.6	-1.0	-1.5	-1.5	-1.3		
	Max	8.2	18.3	9.8	16.1	4.0	5.19	0.62	9.8	18.3	11.7	9.3	1.6	4.10	1.43
	Min	-37.5	-46.3	-34.6	-33.9	-20.3	(0.27)	(0.27)	-46.3	-37.5	-35.7	-33.9	-20.3	(0.39)	(0.08)
Six months	Mean	-8.7	-9.1	-10.7	-8.2	-9.4			-10.7	-8.4	-8.3	-9.7	-7.3		
	Std. dev.	12.6	14.7	17.2	9.3	4.9			15.0	13.8	14.4	12.3	5.0		
	Skewness	-1.9	-1.4	-1.1	-1.1	-0.6			-1.4	-1.5	-1.8	-0.6	-0.9		
	Max	3.0	15.2	24.1	11.3	-3.5	1.95	1.22	3.7	15.2	9.5	24.1	-0.9	2.54	1.28
	Min	-45.9	-51.2	-56.1	-33.5	-17.2	(0.74)	(0.11)	-45.9	-51.2	-56.1	-44.0	-17.2	(0.64)	(0.10)
Nine months[a]	Mean	-11.1	-11.0	-11.5	-10.0	-12.9			-10.3	-10.4	-10.4	-13.8	-8.7		
	Std. dev.	13.6	15.0	17.2	16.5	8.9			14.5	15.6	14.3	18.0	6.5		
	Skewness	-1.6	-1.1	-0.9	-1.8	0.4			-1.2	-1.0	-1.9	-1.1	-1.4		
	Max	2.7	18.7	23.8	10.1	-2.0	1.17	0.46	10.1	18.7	2.7	23.8	-2.0	2.12	1.30
	Min	-42.6	-55.7	-56.0	-62.4	-22.5	(0.88)	(0.32)	-41.9	-55.7	-55.6	-62.4	-22.5	(0.71)	(0.10)
E. Underlying asset is the U.S. dollar															
One month	Mean	-3.3	-1.5	1.9	1.4	3.4									
	Std. dev.	0.0	1.1	1.6	1.8	0.6			-2.5	-0.2	0.6	0.9	2.8		
	Skewness	na	-0.5	1.0	-0.7	na			0.0	2.7	2.4	2.0	0.0		
	Max	-3.3	-0.1	4.0	3.9	4.0	**11.89**	**2.85**	na	1.1	1.7	-0.7	na	3.28	1.33
	Min	-3.3	-3.2	0.2	-2.1	2.8	**(0.02)**	**(0.00)**	-2.5	4.0	3.9	4.0	2.8	(0.51)	(0.09)
Three months	Mean	-6.7	-4.7	5.5	3.8	9.3			-5.0	-3.9	1.1	3.7	8.0		
	Std. dev.	0.0	2.5	2.0	3.6	1.3			0.0	4.5	3.7	5.0	0.0		
	Skewness	na	-0.8	0.5	-0.8	na			na	0.9	1.4	-0.8	na		
	Max	-6.7	-1.7	8.1	8.4	10.6	**14.13**	**3.31**	-5.0	3.2	6.2	10.6	8.0	7.65	**2.51**
	Min	-6.7	-9.2	3.2	-2.9	8.0	**(0.01)**	**(0.00)**	-5.0	-9.2	-2.6	-6.7	8.0	(0.11)	**(0.01)**
Six months	Mean	-14.8	-11.9	5.6	10.3	10.3			-16.2	-10.5	1.4	6.9	14.9		
	Std. dev.	0.0	3.6	6.7	7.9	4.5			0.0	4.7	10.5	10.0	0.0		
	Skewness	na	0.2	-1.1	-0.7	na			Na	0.8	1.0	-0.9	na		
	Max	-14.8	-6.6	12.5	18.5	14.9	**14.10**	**3.49**	-16.2	-3.5	15.5	18.5	14.9	8.81	**2.81**
	Min	-14.8	-16.2	-3.5	-2.1	5.8	**(0.00)**	**(0.00)**	-16.2	-15.5	-9.7	-14.8	14.9	(0.07)	**(0.00)**
Nine months[a]	Mean	-14.7	-15.3	8.0	10.6	16.1			-14.3	-11.5	-0.5	6.5	16.1		
	Std. dev.	0.0	2.3	4.2	8.2	0.0			0.0	8.0	14.4	11.3	0.0		
	Skewness	na	0.7	-1.7	-1.1	na			Na	1.8	0.2	-1.0	na		
	Max	-14.7	-11.3	11.0	19.5	16.1	**13.64**	**3.33**	-14.3	2.1	17.6	19.5	16.1	6.65	**2.55**
	Min	-14.7	-17.7	2.1	-4.2	16.1	**(0.01)**	**(0.00)**	-14.3	-17.7	-17.7	-14.7	16.1	(0.16)	**(0.01)**

[a] The nine-month's results are subject to updates based on future returns.

1a. CARs per technical recommendations



1b. CARs per fundamental recommendations



1c. Payoffs for spread portfolios

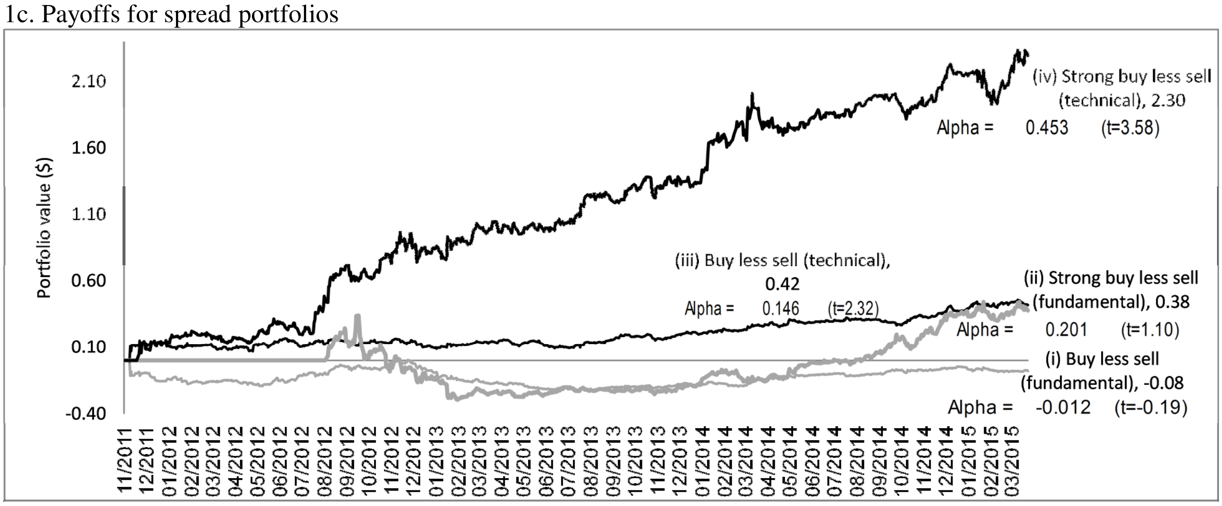
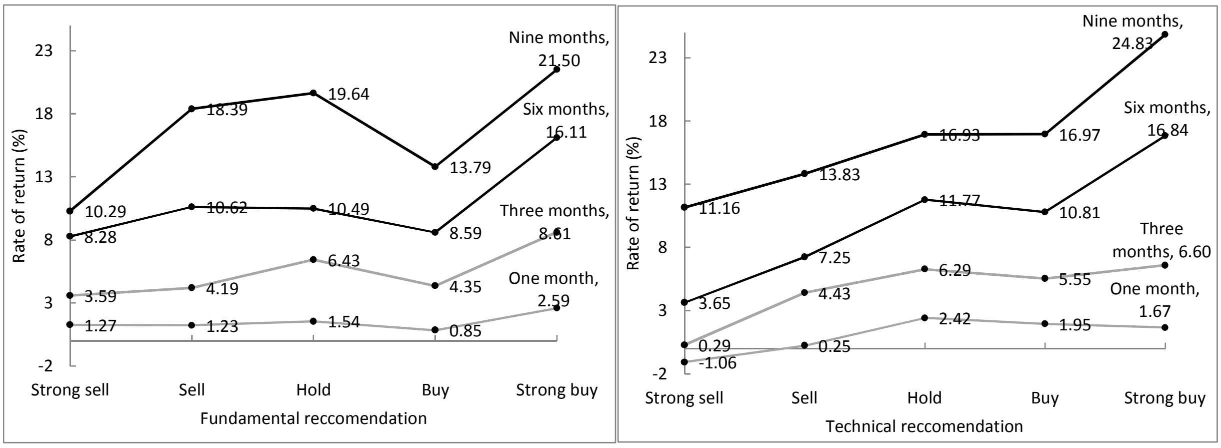


Figure 1. Cumulative abnormal returns (CARs) and portfolio payoffs

The top two panels depict CARs for technical and fundamental recommendations, starting from recommendation broadcast (day zero) and ending nine months (189 trading days) afterward. The *t* statistics on the right-hand side of both panels correspond to the null hypothesis that the nine-month CAR is indistinguishable from zero. H0 null hypothesis asserts that the CAR corresponding to buy and strong buy is not significantly different from that corresponding to sell and strong sell. The bottom panel presents cumulative returns of four zero-cost trading strategies: (i) buy minus sell for fundamental recommendations (ii) strong buy minus strong sell for fundamental recommendations; (iii) buy minus sell for technical recommendations; and (iv) strong buy minus strong sell for technical recommendations. Alpha is the annual Jensen's alpha obtained from regressing portfolio's excess return on the market excess return.

2a. Raw returns



2b. Adjusted returns

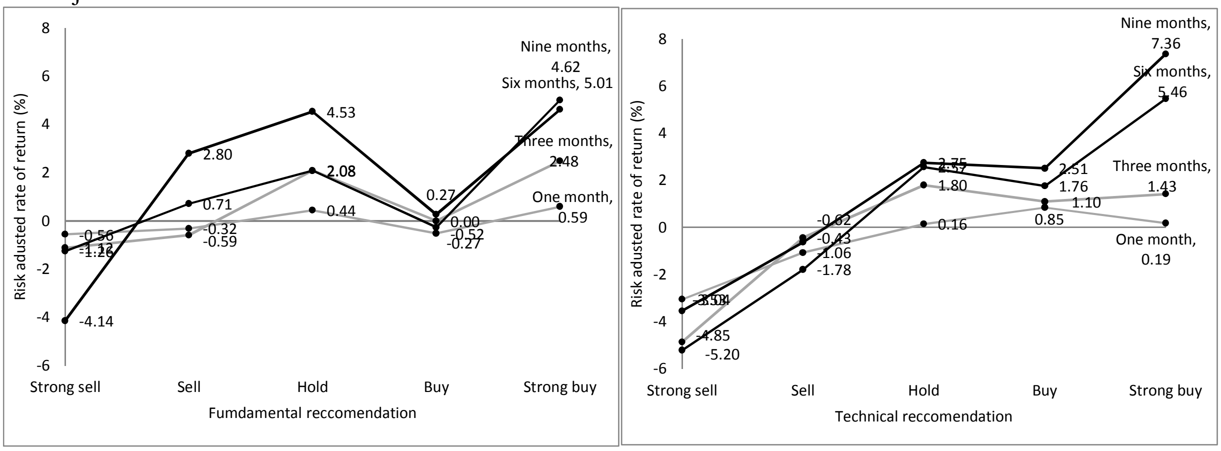
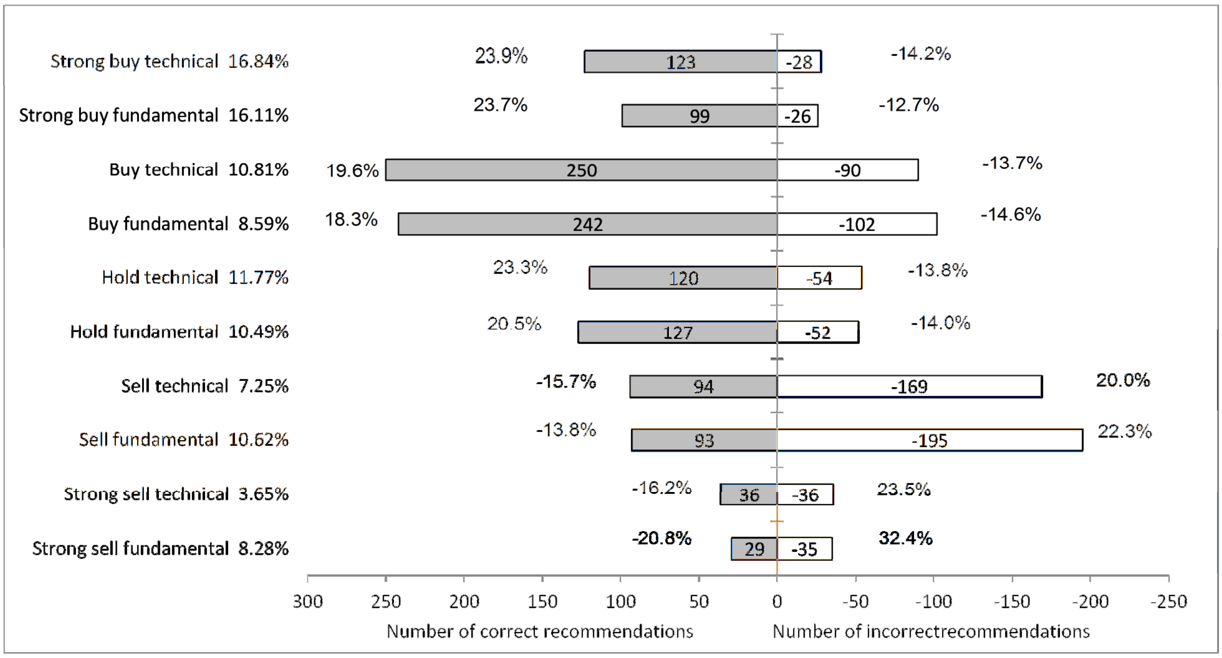


Figure 2. Average stock return per recommendation category

The figure depicts average returns on stocks for strong sell, sell, hold, buy, and strong buy categories. The four curves in each diagram exhibit average returns over one, three, six, and nine months following the recommendations broadcast. Left (right) figures pertain to fundamental (technical) analysis. Top figures exhibit raw returns while bottom figures display returns adjusted for the three Fama-French (1993) and momentum factors.

3a. Raw returns



3b. Risk adjusted returns

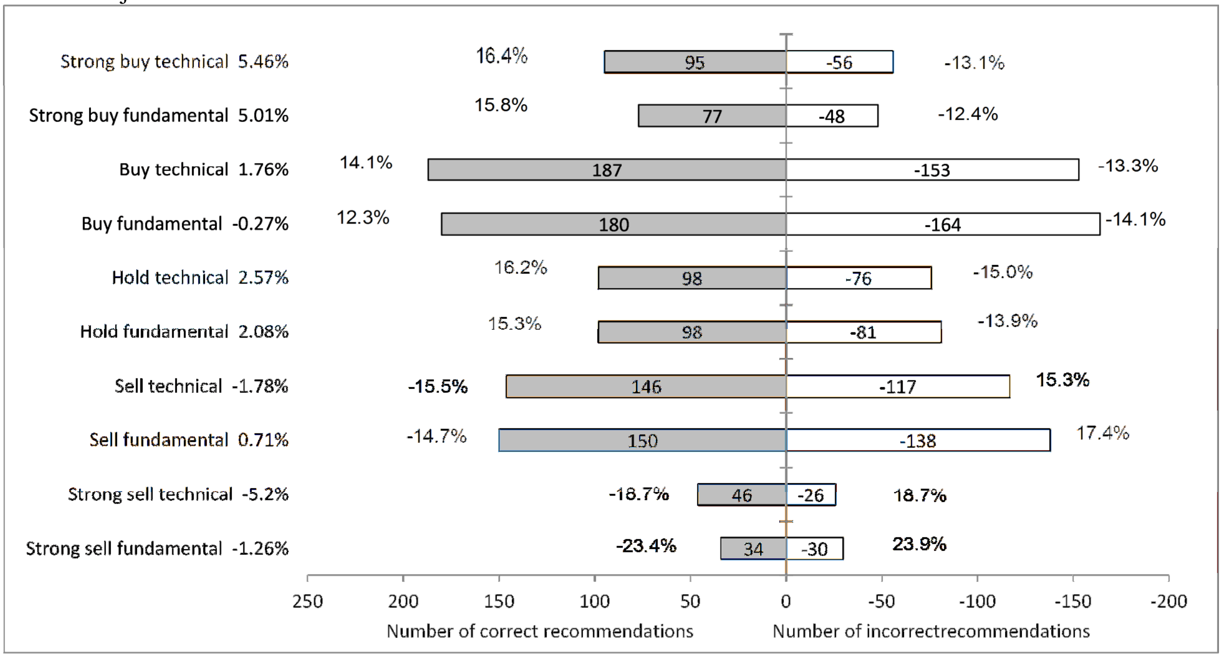
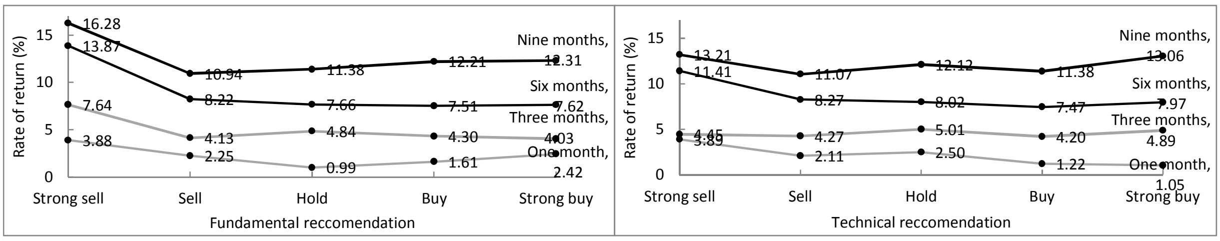


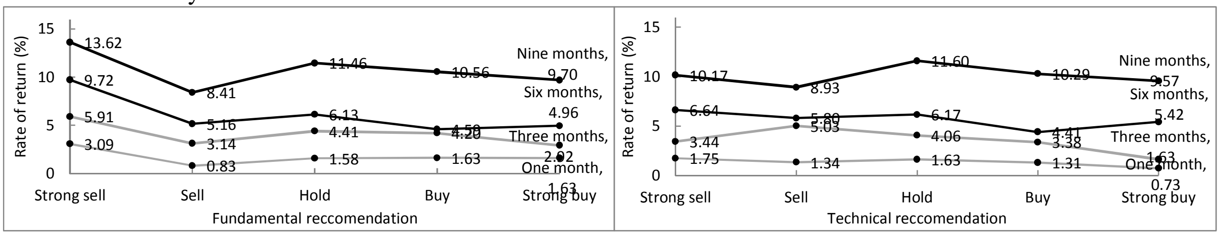
Figure 3. The number of correct and incorrect stock recommendations

The figure reports the number of correct versus incorrect recommendations as well as the average return conditional on correct versus incorrect recommendations for the six-month investment horizon. A correct (incorrect) recommendation amounts to positive (negative) return following hold, buy, and strong buy recommendations or negative (positive) return following sell and strong sell recommendations. The total average return is reported on the left while the conditional average returns are reported near the corresponding bars. Top figure exhibits raw returns while bottom figure displays returns adjusted for the three Fama-French (1993) and momentum factors.

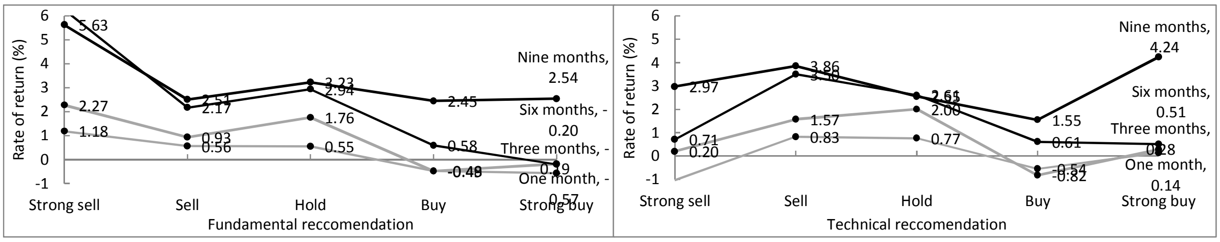
4a. S&P500



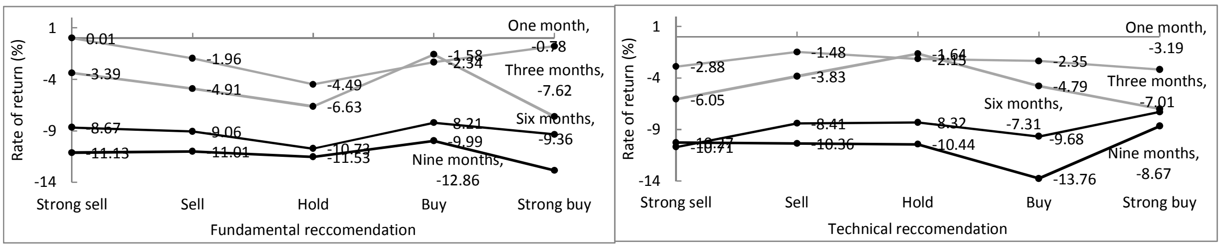
4b. Sector/industry/non-U.S. indices



4c. U.S. bonds



4d. Commodities



4e. U.S. dollar

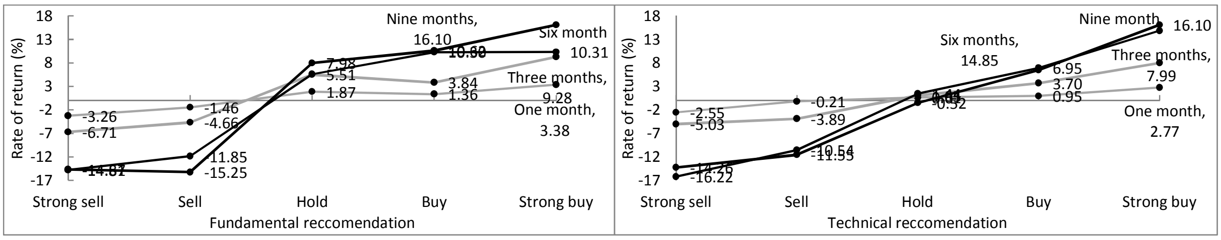
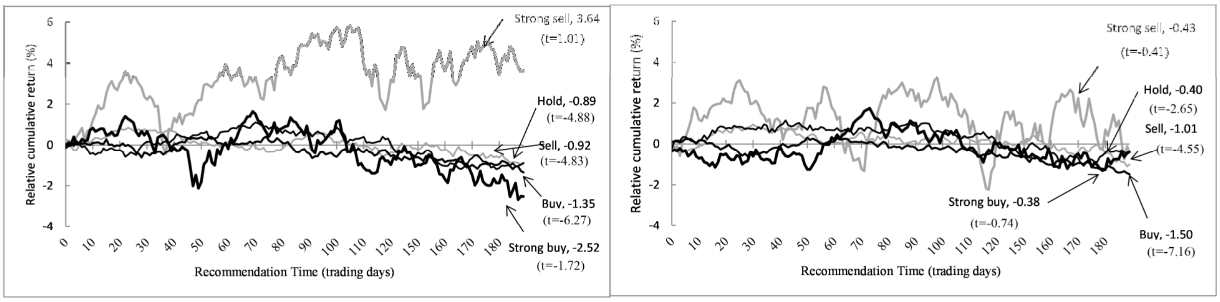


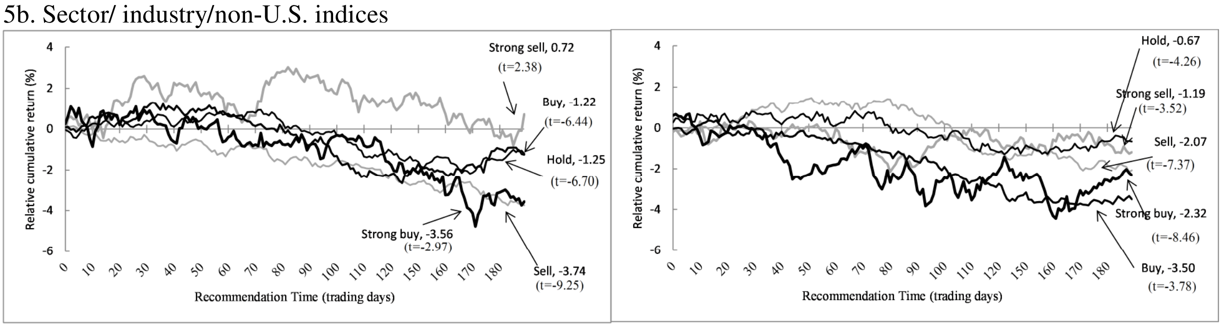
Figure 4. Average returns on various asset classes

The figures present average returns on various assets over one, three, six and nine months after broadcasting fundamental recommendations (left-hand figures) and technical recommendations (right-hand figures). The underlying assets are the S&P500 index, sector/industry/non-U.S. indices, U.S. bonds, commodities and the U.S. dollar exchange rates.

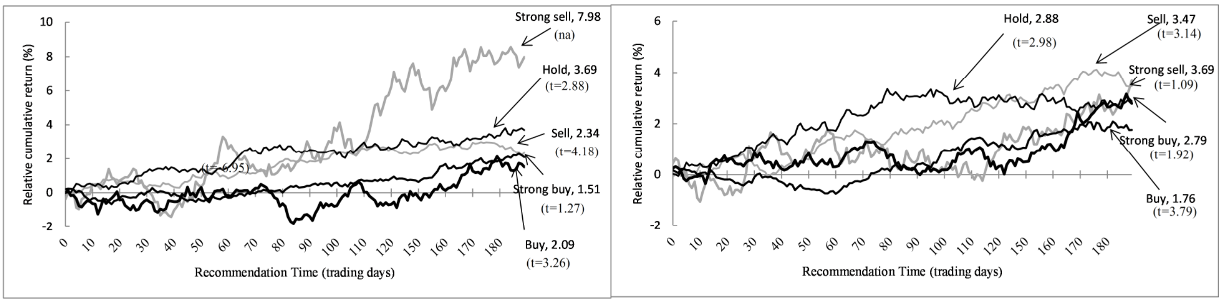
5a. S&P500



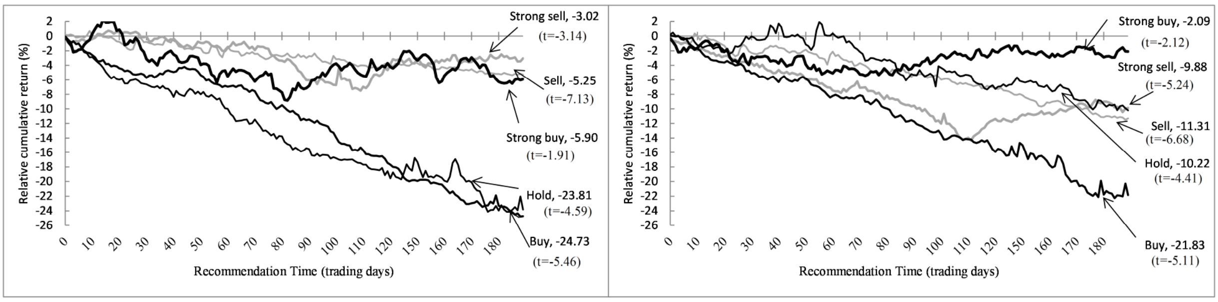
5b. Sector/ industry/non-U.S. indices



5c. U.S. bonds



5d. Commodities



5e. U.S. dollar

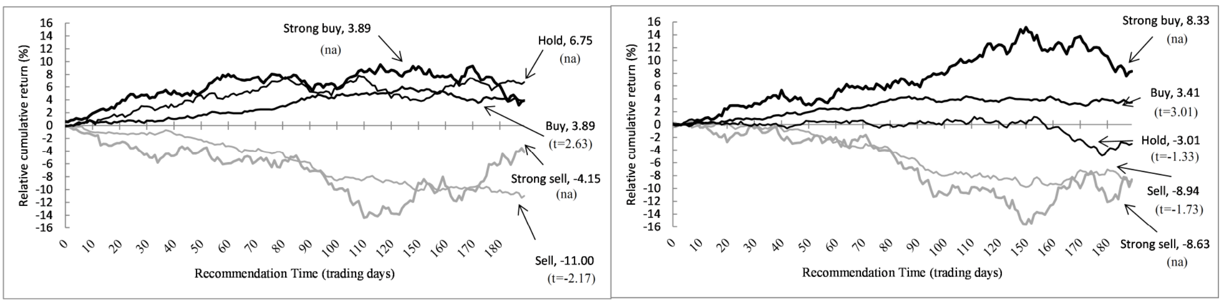


Figure 5. Relative cumulative returns on various asset classess

The figures present comulative returns less the mean return on the S&P500 index, sector/industry/non-U.S. indices, U.S. bonds, commodities and the U.S. dollar for fundamental recommendations (left-hand side figures) and technical recommendations (right-hand side figures). The *t* statistics are in brackets. The null hypothesis asserts that the nine-month comulative return relative to the mean return is not significantly different from zero.

Appendix A. Classification of recommendations

Strong buy

“strong buy”, “time to buy buy buy”, “great buying opportunity”, “I am a big buyer”, “keep buying the stock”, “brilliant buy”, “you have to buy it”, “I’m absolutely a buyer”, “you definitely want to hold it”, “you have to be long”, “you must own it”, “love the asset”, “love the chart”, “we love it”, “I like everything”, “very clear bullish pattern”, “very strong bullish pattern”, “very clear bullish signal”, “very bullish indication”, “very positive”, “very attractive”, “very very bullish setup”, “very optimistic”, “looks phenomenal”, “looks wonderful”, “looks perfect”, “this chart looks like a winner”, “does look very good”, “now it is a great time to own the stock”, “you have to own”, “a lot of reasons to own the stock”, “extremely compelling valuation”, “extremely compelling buy”, “extremely strong”, “fantastic”, “delicious”, “exciting”, “incredible”, “fundamentals are phenomenal”, “great numbers great stock”, “from strength to strength”, “this stock is on fire”, “I am super-fired on the stock”, “the stock is a rock”, “the sky is the limit”, “going to the roof”, “a great place to be”, “extreme oversold”, “bright future”, “uniquely compelling”, “tremendous opportunity”, “does not get better”, “outstanding (technical) position”, “expect high returns”, “going a lot higher”, “continue to run”, “the stock is coiling for a big move up”, “plenty higher prices”, much higher prices”, “plenty room for upside”, “plenty of more upside”, “we’re going to get a big breakout”, and a price target (if given) which at least 20% above the current price.

Buy

“buy”, “we buy”, “it’s a buy”, “I would be a buyer”, “comfort to buy”, “buying opportunity”, “compelling buy on risk reward basis”, “I would buy this chart”, “I am a buyer here”, “you want to buy the sector”, “buy when there is blood in the streets”, “a buying opportunity”, “buyers are going to overwhelm sellers”, “it is a stock to own”, “you want to be long”, “chase it”, “I am long”, “great name to play”, “buy on any pullback”, “the chart says it is a buy”, “constructive chart”, “chart is constructive”, “good chart”, “I expect the chart to head higher”, “I expect the chart to go higher”, “bullish chart”, “bullish continuation patter”, “(bullish) trend is intact”, “bullish flag”, “fairly bullish”, “bearish to bullish reversal”, “mildly bullish”, “relatively bullish”, “very constructive”, “very interesting”, “very nice uptrend”, “very nice opportunity”, “very nice trade”, “very positive sign”, “I see positive signs”, “positive forecast”, “positive on the longer term”, “the trend is positive”, “no sign for a change in (positive) trend”, “no indicator for a change in (positive) trend”, “nice uptrend”, “well-defined uptrend”, “good entry point”, “compelling entry point”, “attractive entry point”, “good time to hold it”, “looks good”, “good investment”, “all good”, “good to be long”, “still looks good”, “good risk-reward”, “decent risk-reward”, “I like it here”, “I like it at this level”, “you can jump in”, “I am on board”, “you want to remain in the sector”, “set to a breakout”, “about to break”, “we are looking for a breakout”, “I think it will go up”, “price will go up”, “expect a rally”, “move higher”, “I expect the stock to move higher”, “the next move is higher”, “headed in the right direction”, “moving above average”, “more upside than downside”, “plenty of upside”, “there is upside potential here”, “strong case for upside”, “sentiment is in favor”, “play the momentum”, “play the momentum from the long side”, “I’m optimistic on it”, “optimistic”, cheap”, “overweight” “quite attractive”, “great leadership”, “solid business”, “strong foundations”, “healthy”, “priced for the bad news”, “oversold”, “will bounce back”, “chance to recover”, “form a bottom”, “back on track”, “a lot of reasons to hold the stock", "I do see value there", and any price target (if given) which is 10%-20% above than current price.

Hold

"hold", "weak hold", "holding pattern", "mixed", "mixed bag", "neutral", "market performance", "market stock", "sector perform", "fairly valued", "fair value", "it's priced fairly", "price is fair", "price target is equal to current price", "equal-weight", "O.K.", "only O.K.", "results are only O.K.", "O.K. shape", "looking O.K.", "right pricing", "boring", extremely boring", "not impressed", "so what?...", "pause", "flat", "I go flat", "a range bound", "be cautious", "I'm cautious ","be careful", "be careful to enter the position", "wait", "wait before buy", "wait for (some value, e.g. 10%) pullback to buy", "wait for a better entry point", "wait until…", "wait to…", "I rather wait", "not something we would buy today but…", "I will not commit more capital", "would not commit new capital", "would not commit fresh capital", "not convinced to buy", "I'm not sure it is time to jump on the wagon", "not a compelling entry level", "not the right entry point", "looking for a catalyst", "we need more information", "need to watch the market response", "we need to see confirmation (for potential trend)", "no catalyst in sight", "could go either way", "inflection point", "indecision", "I don't know how to trade", "anything is possible", "bear and bull tensions", "bear and bull battle", "risk reward proposition is symmetrical", "watch from the sideline", "stay on the sideline", "stay on the sideway", "do nothing", "a little upside", "upside is limited", "there is no upside", "all the good news in the stock", "much of the story is already in price",, "not a great fan of", "not a fan", "I'm not very excited", "not that great", "It is hard to be enthusiastic", "a little speculative", "market got ahead of itself", "close to a buy", "I would not chase it and would not short it", "there are signs of hopes", "a little skeptical", "a little concerned", "I would be a buyer if…(future event, e.g. price goes to…)", "I would be a seller if…(future event)", and recommendation is not clear, recommendation is ambiguous (e.g. "may rally but looks weak", "going to break one side or another", "at a critical point"), recommendation contingents or depends on future event, and contradicting recommendations over mid and long time-horizons within the range of one month and one year.

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Sell

"sell", "will be a seller", "I would be a seller", "it is a sell", "more selling pressure", "selling pressure", "go for the sell", "keep selling", "it is a selling point", "call it a day", "take your money", "out of asset", "I sold it", "I'm out of it", "I would not touch it", "stay away", "avoid this stock", "I would not buy it", "don't buy it", "do not buy!", "definitely not buy", "you are better off buying other assets", this is not a chart I'm going to buy", "I would not buy the stock", "let someone else buy it", "no reason to buy", "we would definitely not buy it", "I would not hold it", "take your money and run", "take some profits", "we avoid", "stay away", "keep away", "I watch from the sidelines", "I stay on the sidelines", "leave it alone", "time to take profits", "trim your profits", "take the money of the table", "I am against the asset", "I do not want to hold it", "it is not the place to put your money", "dislike", "I do not like the odds", "do not like it", "I don't like the risk reward", "not the space you want to be", "do not hold it", "keep away", "lousy stock to own", "not the time to own this stock", "no reason to be involve with", "don't touch it", "I'm out", "further weakness", "there is a downside", "it is going lower", "will go lower", "It's going lower", "price will not hold", "looks bad", "side winds ahead", "bearish chart", "bearish divergence”, “bear market”, “bearish pattern”, “bearish technically”, “I’m bear on this stock”, “I am in the bearish camp”, “(bearish) trend is intact”, “mounting evidence of bearish”, “more bearish than bullish”, “pretty bearish”, “bearish formation”, “a broken chart”, uninspiring chart”, “bull trap”, “(positive) trend reversal”, “vulnerable”, “technically vulnerable”, “stock looks vulnerable”, “gone too far too fast (upward)”, “too far above its trend line”, “this chart is broken”, “the (upward) angle is unsustainable”, “(price) unsustainable”, “very expensive”. “(price) extremely stretched”, “expensive”, “underperform”, “overbought”, “not attractive”, “unjustified price”, “cheap for a reason”, “does not look right”, “pricy”, “price devaluation”, “pricing does not make sense”, “(value) much to rich”, “valuation is tough”, “price far too high”, “(price) too high”, “pricing does not make sense”, “very concerned”, “concerns”, “serious problems”, “negative”, “negative forecast”, “too risky”, “sick”, “I see weakness”, “I see weakness all the board”, “the story only gets worse”, “something is wrong”, “true threat”, “challenging”, “a challenge”, “overdone”, “game over”, “comes to its end”, “dead cat bounce”, “catching a falling knife”, “never try catching a falling knife”, “negative momentum”, “shaky grounds”, “not interested in…”, “going nowhere”, “will lag”, “much better in other names (of companies)”, “no sign for a change in (negative) trend”, “no indicator for a change in (negative) trend”, “hold off”, “expect a decline”, “It’s going down”, “continue to fall”, “continue to go down”, “going to pull back”, “more things to downside”, “we will see a break to the downside”, “a break to the downside is more likely”, “the trend remains down”, “risk-reward tends to be downside”, “momentum is for the downside”, “will probably go lower”, “will probably fall”, “I see weakness continues”, “more downside from here”, “ready to break to downside”, “I expect a large pullback”, “price going down ten percent”, and price target (if given) which is 10%-20% below than current price.

Strong sell

“strong sell”, “I am a seller”, “I would be a seller right here”, “sell and run away”, “dump the stock”, “you want to be a seller”, “you want to be out”, “step off”, “dump the stock”, “I would be aggressive seller”, “get out of it”, “sell with confidence”, “sell short”, “compelling short sell”, “it’s time to bet against the stock”, “massive short”, “I want to be short”, “looking to short it”, “short signal”, “very bearish”, “ultra bearish”, “very bearish setup”, “the chart is a disaster”, “trend is very negative”, “terrible”, “the stock goes straight down”, “going down big time”, “price is going lower!”, “goes from bad to worse”, “going a lot lower”, “big pullback”, “clearly a sell”, “the party is over”, “poised to roundtrip down”, “massively overvalued”, “dead money”, “a failure”, “a broken story”, “uniquely vulnerable”, “streaming to the exit”, “any name but this stock”, “I hate it”, “will not buy it under any circumstances”, the stock worth nothing”, “there is nothing here”, “you want to avoid it”, “downward spiral”, “crappy, a lot of crap”, “the show is over”, and any price target (if given) which is at least 20% below the current price.

Appendix B. Illustration of recommendations classification

Below, we present a program summary published in Yahoo. Based on the strict "stay away" cite we classified the fundamental recommendation as sell. Based on "look very good", "very bullish indication", "plenty of more upside" and "continue to run" the technical recommendation is classified as strong buy. It should be emphasized that we made the classifications according to the full discussion in the program rather than only according to the summary in Yahoo, which is presented here for illustration purpose, as the full discussion usually includes more classification words and additional clarifications.

This hot stock may perk up even more

By Lawrence Lewitinn August 22, 2014 4:31 PM

Shares of Keurig Green Mountain were percolating on Friday thanks to a deal with Kraft Foods. But while the stock has been on fire for the last couple of years, could investors get roasted in the months ahead? Though Keurig Green Mountain's stock is up over 77 percent year-to-date – and has more than quintupled in the last two years – Chad Morganlander, portfolio manager at Stifel Nicolaus Washington Crossing Advisors, is not warm on the stock.

"We at Stifel have a hold recommendation on it," Morganlander said. Stifel Nicolaus makes a market in Keurig Green Mountain's stock. "As a value manager, I believe that this stock is somewhat frothy," said Morganlander, noting that the stock trades around 34 times its 2015 expected earnings. Morganlander is also wary on the company itself. "The business model is somewhat sketchy here when it comes to pricing," he said. "There are competitive issues that they will have in the coming years." Keurig Green Mountain may not be the best investment idea, according Morganlander. "You want to be somewhat more pragmatic about investing in it," he said. "**<u>This is bubblicious to me. Stay away</u>**."

Steven Pytlar, chief equity strategist at Prime Executions, is more optimistic on Keurig Green Mountain based on the technicals. "It does **<u>look very good</u>** on the charts, actually," he said. "Since about the end of 2013, we've seen a number of higher lows develop. And what that means is that the stock is being revalued higher. The market is rewarding that value and paying higher prices." Keurig Green Mountain's breakout above $124 per share on Friday was significant, according to Pytlar. "Since February, people weren't willing to pay more than $124," "In technical terms, that's usually **<u>a very bullish indication</u>**. It usually means there's **<u>plenty of more upside</u>**, and we think that the stock can **<u>continue to run</u>**."

Appendix C. A comprehensive list of all assets featured in “Talking Numbers”

U.S. market
S&P 500, NYSE COMPOSITE INDEX;

Sector/industry/non-U.S. indices
Sector index
S&P100, DOW INDASTRIAL, DOW UTILITIES, DOW TRANSPORTS, NASDAQ COMPOSITE, NASDAQ 100, RUSSEL2000,

Industry index
GUGGENHEIM SHIPPING ETF (SEA), KBW BANK INDEX (BKX), PHLX HOUSING SECTOR INDEX (HGX), MSCI REIT INDEX (RMZ), ALERIAN MLP (AMLP), GOLD MINERS ETF (GDX), JUNIOR GOLD MINER ETF (GDXJ), BROKER DEALERS ETF (IAI), ISHARE NASDAQ BIOTECH (IBB), RUSSELS 2000 ETF (IWM), ISHARE US REAL ESTATE ETF (IYR), ISHARE DJ TRANSPORTATION AVR (IYT), SPDR KBW REG BANKING (KRE), S&P400 MICAP (MDY), OIL SERVICE HOLDERS (OIH), MARKET VECTORS RETAILS (RTH), ISE HOMEBUILDERS INDEX (RUF), MARKET VECTORS STEAL (SLX), SOCIAL MEDIA ETF (SOCL), VANGUARD REIT (VNQ), NYSE ARCA AIRLINE INDEX (XAL), S&P AEROSPACE DEFENCE (XAR), SPDR S&P HOMEBUILDERSA (XHB), ENERGY SPDR (XLE), SPDR FINANCIAL ETF (XLF), INDASTRIAL SELECT SECTOR SPDR (XLI), TECHNOLOGY SPDR (XLK), CONSUMER STAPLE SPDR (XLP), UTILITIES SPDR ETF (XLU), HEALTH CARE SECTOR SPDR ETF (XLV), CONSUMER DICRTIONARY (XLY), SPDR S&P MTLS&MNG ETF (XME), SPDR S&P RETAIL (XRT), ISHARE DJ US HOME (ITB)

Non-U.S. index
NIKKEI 225, SHANGHAI COMPOSITE, S&P BSE SENSEX, ISHARE MSCI INDIA ETF (INDA), HANG SANG, NIGERIA ETF (NGE), ROMENIA BET, VIETNAM ETF (VNM), WISDOMTREE (DXJ), ISHARES MSCI EMERGING MARKETS (EEM), ISHARES MSCI MEXICO (EWW), ISHARE MSCI BRAZIL (EWZ), ISHARE FTSE CHINA 25 (FXI), MARKET VECTORS RUSSIA (RSX), RTS MOSCOW (RTS), ISHARE MSCI TURKEY ETF (TUR), VANGUARD MSCI EUROPE (VGK)

U.S. Stocks
ALCOA (AA), AUTO PARTS (AAP), APPLE (AAPL), ABBOT LABRATORIES (ABT), AUTOMATICE DATA PROCESSING (ADP), AMERICAN EAGLE (AEO), AFLAC (AFL), AIG (AIG), ALLSTATE (ALL), ADVANCED MICRO (AMD), AMGEN (AMGN), AMZON (AMZN), AUTONATION (AN), ABERCROMBIE & FITCH (ANF), AOL (AOL), APACH (APA), ANADARKO PETROLEUM (APC), APPOLO GROUP (APOL), AEROPOSTALE (ARO), ATHENAHEALTH (ATHN), ACTIVISION BLIZZARD (ATVI), AMERICAN EXPRESS (AXP), ASTRAZENCA (AZN), AUTOZON (AZO), BOEING (BA), BANK OF AMERICA (BAC), BED BATH & BEYOND (BBBY), BLACKBERRY (BBRY), BEST BUY (BBY), BARCLAS (BCS), SOTHBY'S (BID), BIOGEN IDEC (BIIB), BARNESS & NOBLE (BKS), BURGER KING (BKW), BRISTOL MYERS (BMY), BRITISH PETROLIUM (BP), BUFFALO WILD WINGS (BWLD), CITI GROUP (C), CABELA'S (CAB), CONAGRA (CAG), CHEESECAKE FACTORY (CAKE), CATERPILLAR (CAT), CHUBB (CB), CBS CORP (CBS), CARNIVSAL (CCL), CHESAPEAKE ENERGY (CHK), CLIFF NATURAL (CLF), COLONY FINANCIAL (CLNY), COMCAST (CMCSA), CHIPOTLE (CMG), CABOT OIL AND GAS (COG), COACH (COH), CONOCOPHILLIPS (COP), COSTCO (COST), CAMBELL SOUP (CPB), CARTER'S (CRI), SALESFORCE (CRM), CICO (CSCO), CINTAS (CTAS), CVS CAREMARK (CVS), CHEVRON (CVX), CEASARS (CZR), DOMINION RESOURCES (D), DELTA AIR LINES (DAL), DUPONT (DD), 3D SYSTEMS (DDD), DEERE (DE), DELL (DELL), DIAGEO (DEO), DOLLAR GENERAL (DG), D.R. HORTON (DHI), WALT DISNEY (DIS), DISH NETWORK (DISH), DUNKIN BRANDS (DNKN), DIMOND OFFSHORE (DO), DR PEPPER (DPS), DOMINO'S (DPZ), DARDEN RESTAURANT (DRI), DIRECTTV (DTV), DEVON ENERGY (DVN), DREAMWORKS (DWA), ELECTRONICS ART (EA), EBAY (EBAY), CONSOLIDATED EDISION (ED), ENTERPRISE PRODUCTS (EPD), EQUITY RESIDENTIAL (EQR), EXPEDIA (EXPE), FORD (F), FACEBOOK (FB), FREEPORT MCMORAN (FCX), FAMILY DOLLAR (FDO), FEDEX (FDX), FREDDIE MAC (FMCC), FREDDIE MAC (FNMA), FOSSIL GROUP (FOSL), TWENTY-FIRST CENTURY FOX (FOXA), FIRST SOLAR (FSLR), GENERAL DYNAMIC (GD), GENERAL ELECTRIC (GE), GILEAD

SCIENCES (GILD), GENERAL MILLS (GIS), GENERAL MOTORS (GM), GREEN MOUNTAIN (GMCR), RANGOLD RESOURCES (GOLD), GOOGLE (GOOG), GOPRO (GPRO), GAP (GPS), GARMIN (GRMN), GROUPON (GRPN), GOLDMAN SACHS (GS), HALLIBURTON (HAL), HOME DEPOT (HD), HEBALIFE (HLF), HRLEY-DAVIDSON (HOG), HOVNANIAN (HOV), HEWLETT PACKARD (HPQ), H&R BLOCK (HRB), HERTZ GLOBAL (HTZ), HUMANA (HUM), IBM (IBM), ICAHN ENTERPRISES (IEP), IMAX (IMAX), INTEL (INTC), INVENSENSE (INVN), INTUITIVE SERGICAL (ISRG), JETBLUE (JBLU), J.C. PENNEY (JCP), JOHNSON & JOHNSON (JNJ), JUNIPER NETWORKS (JNPR), JOS A BANK (JOSB), JPMORGAN (JPM), NORDSTROM (JWN), KB HOME (KBH), KRISPY KREME (KKD), COCA-COLA (KO), MICHAEL KORS (KORS), KANSAS CITY SOUTHERN (KSU), LYBERTY GLOBAL (LBTYA), LENNAR (LEN), LIONS GATE (LGF), LOCKHEED MARTIN (LMT), LINKEDIN (LNKD), LORILLARD INC (LO), LOWE'S (LOW), LUFKIN INDUSTRIES (LUFK), LULULEMON (LULU), SOUTHWEST AIRLINES (LUV), LAS VEGAS SANDS (LVS), MACY'S (M), MASTERCARD (MA), MACERICH (MAC), MATTEL (MAT), MCDONALD'S (MCD), KRAFT (KFT/MDLZ), MGM RESORTS (MGM), MONSTER BEVERAGE (MNST), ALTRIA (MO), MARATHON PETROLIUM (MPC), MERK (MRK), MORGAN STANLEY (MS), MICROSOFT (MSFT), MADISON SQUARE (MSG), MICRON TECHNOLOGY (MU), MURPHY OIL (MUR), NAVISTAR (NAV), NASDAQ OMX (NDAQ), NOODLES (NDLS), NEWMONT MINING (NEM), NETFLIX (NFLX), NICE SYSTEMS (NICE), NIKE (NKE), NOKIA (NOK), NORFOLK SOUTHERN (NSC), NUANCE COMM (NUAN), NYSE EURONEXT (NYX), OLD MOMINION FREIGHT (ODFL), OMNICOM GROUP (OMC), ORACLE (ORCL), OUTERWALL (OUTR), ORBITZ (OWW), OCCIDENTAL PETROLEUM (OXY), PANDORA (P), PRICELINE (PCLN), PEPSICO (PEP), PFRIZER (PFE), PROCTOR & GAMBLE (PG), PULTEGROUP (PHM), PVH (PVH), QUALCOMM (QCOM), ROYAL CARIBBEAN (RCL), ROYAL DUTCH SHELL (RDS-A), REVLON (REV), TRANSOCEAN (RIG), RALPH LAUREN (RL), REALIGY HOLDINGS (RLGY), ROSS STORES (ROST), SPRINT (S), STARBUCKS (SBUX), SOLARCITY (SCTY), SEAWORLD (SEAS), SEARS (SHLD), SHERWIN WILLIAMS (SHW), SIRIUS XM RADIO (SIRI), SIX FLAGS (SIX), SAKS (SKS), SKECHERS (SKX), SCHLUMBERGER (SLB), SANDISK (SNDK), SONY (SNE), SODASTREAM (SODA), SONIC (SONC), STAPLES (SPLS), CONSTELLATION (STZ), AT&T (T), MOLSON COORS (TAP), TASER INTERNATIONAL (TASR), TAUBMAN CENTERS (TCO), TARGET (TGT), TIFANY (TIF), TOYOTA (TM), TOLL BROTHERS (TOL), TRIPADVISOR (TRIP), TRINITY INDUSTRY (TRN), TRAVELERS (TRV), TESLA (TSLA), TESORA (TSO), TAKE TWO INTER (TTWO), TIME WARNER CABLE (TWC), TWITTER (TWTR), TIME WARNER (TWX), TEXAS INSTRUMENTS (TXN), UNDER ARMOUR (UA), UNITED CONTINENTAL (UAL), UBS (UBS), UNITED HEALTHCARE (UNH), ULTRA PETROLEUM (UPL), UNITED PARCEL SERVICE (UPS), URBAN OUTFITTERS (URBN), USB (USB), UNITED TECHNOLOGIES (UTX), VISA (V), VIACOM INC (VIAB), VALERO ENERGY (VLO), VODAPHONE (VOD), VERIZON (VZ), WEBMD HEALTH (WBMD), WENDY'S (WEN), WELLS FARGO (WFC), WHOLE FOODS (WFM), ANTM (WLP), WAL-MART (WMT), WEINGARTEN REALITY INVESTORS (WRI), WORLD WRESTLING (WWE), WYNN RESORTS (WYNN), US STEAL (X), EXXON MOBIL (XOM), YELP (YELP), YAHOO (YHOO), YUM BRANDS (YUM), ZILLOW (Z), ZINGA (ZNGA)

U.S. Bonds
10-YR T-NOTE (iShares 7-10 Year Treasury Bond ETF -IEF (94US10Y)
ISHARE S&P NATIONAL MUNI (MUB)
BARCLAYS MUNI BOND (TFI)

Commodities
GOLD COMEX (GCZ4), SILVER COMEX (SIZ4), COPPER (HGZ4), NATURAL GAS (NGV14), PALLADIUM (PAL), BRENT CRUDE OIL (BRENT), RABOB GASILINE (GASOLINE), WTI CRUDE OIL (WTI), CORN (CORN), ORANGE JUICE (ORNG), WHEAT (WHEAT), DEUTCHE BANK COMMODIDITIIES ETF (DBC), SPDR GOLD ETF (GLD), IPATH DJ-UBS COFFEE (JO), SILVER ETF (SLV), NATURAL GAS FUND (UNG), CRP INDEX

FORX
DOLAR INDEX, YEN-DOLAR, DOLAR-EURO, DOLAR-RUPPY

Others
VIX, RENAISSANCE IPO ETF (IPO), BITCOIN, NYC REAL ESTATE, LUXORY HOUSES, JUNK BONDS ETF, ALIBABA IPO, MORTGAGE RATES