Talking Numbers:

Technical versus Fundamental Investment Recommendations

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Abstract:

This paper studies the real-time value of technical and fundamental investment recommendations broadcasted simultaneously on the TV show "Talking Numbers." Considering individual stocks, technicians outperform leading fundamental analysts in predicting upward and downward price movements over investment horizons of one to twelve months. Technicians also deliver a significant alpha with respect to the Fama–French and momentum benchmarks. Regarding market indexes, other equity indexes, Treasuries, and commodities, both technicians and fundamental analysts deliver poor forecasts. The evidence supports the notion that technicians can detect insider buying and selling of individual stocks, whereas fundamental analysis is virtually worthless.

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 database from "Talking Numbers" to assess the value of technical and fundamental analyses. Hosted by CNBC and Yahoo, "Talking Numbers" is a TV show that confronts the investment recommendations of leading technicians and fundamental analysts. The show provides a unique setup for understanding the value of financial analysis. In the first place, the head-to-head simultaneous recommendations of technicians and fundamental analysts on the same assets over similar investment horizons establish an ideal laboratory in which to compare the relative worth of the two investment approaches. As both schools of thought are exposed to the same public information during the broadcast, we are able to examine the extent to which technicians and fundamental analysts possess private information and are able to detect insider trading and process the flow of public information effectively.

Moreover, the analysis of dual recommendations is robust to several biases characterizing the studies of analysts' forecasts. First, the show participants are well positioned and thus less prone to experience and reputation concerns (Graham, 1999; Sorescu and Subrahmanyam, 2006) as well as career concerns (Hong et al. 2000; Clement and Tse, 2005). Second, the simultaneous recommendations eliminate potential cross-herding between analysts. Third, our experiments are fairly robust to data-mining. To our knowledge, we are the first to visit the recommendations broadcasted in "Talking Numbers" as well as the first to assess the performance of technical recommendations, as the vast literature on technical analysis has studied technical rules.

Overall, we study 1620 dual recommendations (1000 recommendations for 262 individual stocks and 620 for other assets). The recommendations cover the largest stocks (e.g., Apple, Google, Exxon Mobil), the most liquid commodities (e.g., gold, oil), the main exchange rates (e.g., the U.S. dollar), the major bonds (e.g., the U.S. ten-year notes), the major equity indexes (e.g., the various Dow Jones indexes) and prominent sectors (e.g., technology, real estate, pharmaceutical). Thus, our experiments are fairly robust to liquidity concerns or the presence of extreme observations.

Figure 1 highlights the major findings for technical and fundamental individual stock recommendations during the sample period from November 2011 through December 2014. It plots 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). In particular, we consider buy-minus-sell and strong-buy-minus-strong-sell technical and fundamental portfolios.

[Please insert Figure 1 here]

The evidence shows that technicians display rather impressive stock-picking skills, recommending the purchase of undervalued stocks along with the sale of overvalued stocks, while fundamental analysts provide no value whatsoever. To illustrate, observe from Panel A that the twelve-month CARs of the strong-sell, sell, hold, buy, and strong-buy technical recommendations are –8.13%, –0.59%, –0.10%, 1.56%, and 8.97%, respectively. In contrast, Panel B shows that the CARs attributable to fundamental analysis do not align with the type of recommendation. If anything, the sell recommendations generate higher CARs 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-strong-sell portfolio rotates around zero. In contrast, the value of the two corresponding technical portfolios is positive and tends to increase with the investment horizon. Specifically, over the sample period, the buy-minus-sell portfolio value is \$0.42 for the \$1 initial long and \$1 initial short positions, recording an annual CAPM alpha of 14.8% (t = 2.35). More prominently, the value of the strong-buy-minus-strong-sell portfolio is \$2.30, recording a strikingly large annual alpha of 45.3% (t = 3.58). Accounting for the trading costs upon entering and exiting a position, the threshold cost that would set the alpha of the buy-minus-sell (strong-buy-minus-strong-sell) portfolio to zero is 0.62% (2.91%) per transaction. Of course, such large alphas emerge from a short sample period. Attempting to extrapolate those alphas to considerably longer periods would be excessive. Nevertheless, technical recommendations seem to add value in predicting both upward and downward stock price movements. The latter is perhaps more convincing given the positive trend characterizing financial markets during the sample period.

Further analysis shows that technicians outperform in two dimensions. First, they generate a higher proportion of correct recommendations, whereby a correct recommendation amounts to a buy (sell) recommendation followed by an advancing (diminishing) stock price. Second, they produce higher gains following correct recommendations and lower losses following incorrect recommendations. Consistently, for time horizons ranging from one month to twelve months, positive buy and strong-buy technical recommendations are followed by higher returns than buy and strong-buy fundamental recommendations. Likewise, negative sell and strong-sell technical recommendations are followed by lower returns than the corresponding fundamental recommendations. The success of technicians in picking individual stocks is robust to controlling for common risk factors as well as for firm-level size, book-to-market, volatility, trading volume, and past trends in stock prices. It is also unaffected by the analyst's gender, by the immediate impact of the broadcast on the stock price (which is found to be highly significant), and by reasonable trading costs. As an aside, there are only 10% females among both technicians and fundamental analysts. Within this subsample of female analysts, the evidence also shows significant outperformance of technical recommendations.

We demonstrate that the inability of fundamental analysts to predict future returns of individual stocks is uniform across various industries (excluding services) and across all the equity styles considered, namely size, book-to-market, past return, and volatility. 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 the participants in "Talking Numbers" to predict future commodity prices. In fact, both schools of thought have uniformly failed to predict returns on all the broader asset classes, for example Treasuries, market indexes, and equity sector indexes.

The difference in performance among individual stocks versus broad indexes could be attributable to arbitrage capital in that investable patterns in broad market indexes immediately attract capital and thus are traded away. Moreover, common wisdom suggests that the abilities to process public information effectively or extract private signals from prices and volume mostly characterize individual stocks. Indeed, in his bestseller on technical trading *The New Trading for*

Living, Elder (2014) points out (page 36) that "Charts reflect all trades by all market participants – including insiders. … Technical analysis can help you detect insider buying and selling." Of course, such (illegal) insider trading pertains to individual stocks only.

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 (1992) and Womack (1996) document value in revisions of consensus recommendations, while Barber et al. (2001) report the disappearance of that value in the presence of transaction costs. Likewise, Jaffe and Mahoney (1999) and Metrick (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, fundamental analysts 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 could reveal the presence of private information, and Zhu and Zhou (2009) show that combining the 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 the Dow rules exhibit some predictive ability. Brock et al. (1992) find that technical rules predict returns on stock indexes. However, such predictability vanishes in the presence of transaction costs, according to Bessembinder and Chan (1998). Allen and Karjalainen (1999) and Sullivan et al. (1999) do not find substantial value in technical rules, while Lo et al. (2000) show that technical patterns predict stock returns. Han et al. (2013) report profitability based on moving averages, 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 publicized technical rules. Thus, we consider the possibility that the technicians participating in the show use propriety technical rules.

The third strand examines the immediate impact of media-publicized recommendations. Liu et al. (1990), Barber and Loeffler (1993), and Mathur and Waheed (1995) 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 a newsgroup on the Internet. Neumann and Peppi (2007) find that the 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 on the CNBC "Morning Call" and "Midday Call" programs produce abnormal immediate profits within 15 seconds. Relative to these studies, we examine the longer-term value, rather than the immediate impact, of recommendations. Eventually, technical stock recommendations provide value not only for immediate trading, but also for a few months, up to a year, following the broadcast.

Indeed, to our knowledge, we are the first to confront fundamental analysts and technicians. 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 for similar investment horizons, and the collection of assets covered is comprehensive. A remaining task is to shed more light on the outperformance delivered by technical stock recommendations. In active asset management, performance reflects stock-picking and benchmark-timing skills, where stock-picking skills could further be attributable to industry and/or style rotation. Economic theory (e.g., Admati et al. 1986) typically formulates skills through the managerial ability to process private signals. Empirically, however, one cannot conclude whether a positive-alpha fund manager possesses private information or whether that manager perhaps 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 control for those factors characterizing the risk–return trade-off; further, they are likely to misspecify the nature of time variation in both benchmark loadings and risk premiums, if there is such time variation.

In the context of technical recommendations, we rule out the possibility of market timing, industry rotation, or style rotation. Certainly, technicians fail to predict returns on market, sector, and other broad indexes. Putting aside bad-model concerns, technicians could indeed process public information more effectively through their investment toolkits. As noted earlier, using various charts, technicians can help to detect buying and selling insider (illegal) trading. Detecting insider buying (selling) helps to predict upward (downward) moves in individual stock prices.

The remainder of the paper is organized as follows. Section 2 explains the nature of the "Talking Numbers" broadcast and the participating analysts as well as the methodology used to convert the content of the show into ultimate investment recommendations. Section 3 describes the data. Section 4 reports the empirical findings corresponding to individual stocks. Section 5 extends the analysis to the other asset classes noted earlier. Section 6 concludes. A list of the assets covered in the show and the recommendation classification system are detailed in the appendices.

2. Methodology

Our technical and fundamental recommendations are extracted from the media broadcast entitled "Talking Numbers." Prior to May 2013, the program was exclusively hosted by the CNBC television network. Since May 2013, CNBC and Yahoo Finance have jointly hosted the show. According to 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 the stocks of prominent U.S. corporations that are about to post financials, hot sectors, hot markets, and general assets experiencing substantial price fluctuations (e.g., the recent drop in commodity prices and the rise in the U.S. dollar).

The technicians and fundamental analysts participating in the show usually serve as the heads of research or the investment division of highly regarded banks, investment management funds, and research companies, such as Deutsche Bank, Piper Jaffray, Stifel Financial Corp. and Standard & Poor's Investment Advisory Services. Based on browsing through participants' résumés, the typical analyst possesses about twenty years of experience, a position as a managing director or chief officer and nominations in ranking tables for best analysts, portfolio managers or technicians. A significant portion of the participants are at the advanced career stage of founding their own companies.

Fundamental analysis typically starts with a macroeconomic outlook and industry conditions, followed by a recommendation along with supporting discussions. A technician, in most cases, describes a chart of historical prices along with moving averages. He/she 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 for the technician, the fundamental analyst, and the show hosts to debate the nature of the recommendations.

As noted earlier, 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 April 2015, the original program was discontinued, and CNBC initiated a new broadcast titled "Trading Nation." This new show exhibits several similarities to "Talking Numbers," including the same host. In addition, several analysts who participated in "Talking Numbers" also take part in "Trading Nation." However, the new format of "Trading Nation" does not formally confront technical and fundamental points of view.

In the first year of the sample, "Talking Numbers" was broadcasted once per trading day, typically featuring four recommendations or two dual recommendations: two distinct assets, each of which is covered by both technicians and fundamental analysts. Then, the program was usually broadcasted several times daily, in most cases each program covering a single asset. In a few cases, the program features only one analyst delivering either a technical or a fundamental point of view, without a comparison. Such single recommendations are excluded from the primary analysis and are later considered when examining the robustness of the results.

We classify technical and fundamental recommendations into five conventional categories, namely "strong buy," "buy," "hold," "sell", and "strong sell." In about 20%–30% of the cases (depending on the asset class), the analyst's formal rating was explicitly stated verbally or in a caption. Then, the classification clearly adhered to the 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 all the programs twice and classified them 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. In either case, the distinction between positive recommendations and negative recommendations is crystal clear.

Appendix A provides the full list of terms characterizing the five recommendation categories, while Appendix B illustrates how specific programs were classified. Below, we provide a comprehensive discussion.

The strong-buy category features distinct and enthusiastic recommendations to buy an asset without any reservation. Any expectation of at least a 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 anybody 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 starting to buy the asset and increase buying as a pullback emerges, such an explicit recommendation would be classified as a buy. However, if an analyst recommends waiting for a pullback and only then buying the asset, that contingent recommendation would be classified as a hold.

The strong-sell category consists of distinct recommendations to sell the asset immediately without any reservation, which is occasionally even accompanied by a suggestion to sell it short. Any expectation of at least a 20% price drop during the coming year falls within this category. The sell category features a sell recommendation with reservations that do not deter anybody 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 performing" and "neutral." To avoid subjective judgment biases and misinterpretation, we attribute mixed, contingent, ambiguous, and contradictory recommendations to the hold category. This classification guarantees that the buy and sell categories are unambiguous and transparent.

While the differences between strong-buy and buy and between strong-sell and sell recommendations could be subtle, the distinctions between the buy and the 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), or a two-category scale (all buy and all sell, excluding hold).

Several additional notes are in order. First, we considered only recommendations corresponding to "investment" horizons, ranging from a few months to one year, which are provided in all the programs. However, in a few programs, analysts also provide a separate recommendation for a time horizon of one day or a few days, usually referred to 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 discarded short-term and long-term recommendations. Second, while discussions about the market index (S&P 500) often include both negative and positive aspects and tones, single-stock discussions are more distinctive and clear with technical discussions that are typically more transparent and stricter than fundamental ones.

3. The data

For broadcasts 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 employed several net-searching practices to detect programs that were missing from the main data archives. The main source of programs after the merge is Yahoo Finance at finance.yahoo.com. This source is organized chronologically and contains all the post-merger programs. Overall, we were able to cover the vast majority, if not all, of the "Talking Numbers" recommendations during the sample period.

Table 1 summarizes the descriptive statistics of the broad set of recommendations for single stocks, the market index, particular equity sectors, bonds, commodities, and currencies. Appendix C presents the full list of all the individual stocks featured in "Talking Numbers" as well as all the other assets. Altogether, we were 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&P 500 index (the NYSE composite index in one case); 256 dual recommendations corresponding to 58 indexes and ETFs, such as the NASDAQ 100, the Dow Jones Industrial/Utilities/Transportation and 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 10-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 3 other currencies and 1 basket of currencies. In 370 shows, a single recommendation records no corresponding comparison, because either only one analyst participated in the show or one of the analysts did not ultimately discuss the relevant asset. As noted in the previous section, such recommendations were excluded from the main analysis but are later considered in the robustness tests. A total of 28 observations were excluded as the underlying asset is unique (e.g., Bitcoin, VIX, luxury houses).

Observe from Table 1 that while the number of technicians and fundamental analysts is quite similar among the general asset classes, it is markedly distinct among single stocks. There are 34 technicians 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 the recommendations span all 5 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 with the numbers from 1 to 5 (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 equity sectors and non-U.S. indexes, 0.29 for bonds, and 0.38 for commodities. Technical and fundamental recommendations are closely related in predicting exchange rates, recording a Spearman correlation coefficient of 0.51. Likewise, Pearson'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. The stock return and trading volume figures are from the Center of Research in Security Prices (CRSP). The firm accounting variables, such as the book value, are from Compustat. The earnings surprises are based on the Institutional Brokers' Estimate System (I/B/E/S). The Fama–French (1993) and momentum factors, used to risk-adjust investment returns, are provided by Kenneth R. French's library. The stock indexes covered by "Talking Numbers" are provided by the S&P Dow Jones Indexes, NASDAQ OMX Global Indexes, Nikkei, Moscow Exchange, Bucharest Stock Exchange, and International Securities Exchange (Homebuilders Index).

The prices of precious metals are provided by the London Bullion Market Association. The natural gas prices are from the U.S. Energy Information Administration (EIA). The copper prices are provided by the New York Mercantile Exchange, the agriculture prices are from CME Group and Intercontinental Exchange (ICE) and the source for the CRB Index is Thomson Reuters. All the other commodity prices are from the Federal Reserve Bank of St. Louis. The 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.

The interest rates are also provided by the Federal Reserve Bank of St. Louis. The 90-day Treasury bill rate serves as a proxy for the risk-free rate. To measure the performance of 10-year

Treasuries recommendations, we employed two methods. First, the ten-year Treasury Constant Maturity Rates were used to calculate the price of a notional zero-coupon 10-year bond. Second, we employed the price of the iShares 7–10 Year Treasury Bond ETF. As the empirical evidence for the two methods is similar, we report the findings for the first approach.

4. Individual stocks: the empirical evidence

This section focuses exclusively on single-stock recommendations. The other asset classes will be analyzed in the next section. Figure 2 depicts the average stock returns for the five recommendation categories. We consider investment horizons of one, three, six, nine, and twelve months following the broadcasts. To be on the conservative side, here as well as in all the follow-up analyses, investment returns start accumulating based on the recommendation day's closing price. The left (right) figures pertain to fundamental (technical) recommendations. The top figures exhibit raw average returns, while the bottom figures display returns adjusted for the three Fama–French and momentum factors.

Consistent with the findings reported in the introduction, it is evident from Figure 2 that the fundamental analysts have not been successful in predicting stock returns. The mean raw returns during one, six, nine, and twelve months following sell recommendations are actually higher than the mean returns following buy recommendations. For the twelve-month horizon, the mean returns associated with sell and buy recommendations are 23.39% and 20.29%, respectively. The corresponding risk-adjusted figures are 2.38% and 1.87%. In contrast, the technical analysis reveals a rather strong return–recommendation relation. Focusing on the six-month horizon, the average returns are 3.65% (strong sell), 7.25% (sell), 11.77% (hold), 10.86% (buy) and 16.84% (strong buy). The risk-adjusted figures are –5.21% (strong sell), –1.78% (sell), 2.57% (hold), 1.82% (buy), and 5.46% (strong buy).

[Please insert Figure 2 here]

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

Starting with the fundamental analysts, sell recommendations are followed by higher average returns than buy recommendations for the one-, six- and nine-month horizons. For instance, for the nine-month horizon, sell (buy) recommendations record an 18.3% (13.7%) average return. A comparison of the strong-buy and strong-sell fundamental recommendations reveals a more appealing outlook. The return spreads between the two extreme categories are $2.6\% - 1.3\% = 1.3\%$, 5.0%, 7.8%, 10.4%, and 17.9% for the five investment horizons. Such spreads may appear to be inconsistent with the payoff description (Figure 1c) of the strong-buy-minus-strong-sell portfolio. Notice, however, that prior to August 2013 there are no records of strong-sell recommendations. For the next few months afterwards, there is 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-strong-sell portfolio is largely influenced by the rare appearance of fundamental strong-sell recommendations at the beginning of the sample.

Nevertheless, our overall findings are consistent in that the return spreads between all-buy and all-sell fundamental recommendations are relatively small, given by 0.1%, 1.4%, 0.3%, –1.2% and 1.3%, respectively. Likewise, for the 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, the technicians reveal impressive stock-picking skills. Their buy recommendations predict uniformly higher average returns, both raw and risk-adjusted, than their sell recommendations. For instance, for the nine-month horizon, buy and sell recommendations are associated with a 16.5% and 13.9% average raw return, respectively. The corresponding risk-adjusted figures are 2.4% and –0.6. Further, the return spreads between all-buy and all-sell recommendations are equal to 1.9%, 2.4%, 6.2%, 5.7% and 6.4% for the five horizons considered. Similar evidence emerges on the basis of risk-adjusted returns. The investment returns following all-buy recommendations are uniformly larger than those following all-sell recommendations. For example, the corresponding nine-month returns are –1.2% for all-sell and 3.9% for all-buy. The superiority of technicians over fundamental analysts appears in all five time horizons. In all cases, the average returns corresponding to technical all-sell recommendations are lower than the fundamental all-sell recommendations and the average returns corresponding to technical all-buy recommendations are higher than the fundamental all-buy recommendations.

All the statistical tests pertaining to the technical recommendations are highly significant, indicating that the success of the technicians is not random. Specifically, among the technical recommendations, the Kruskal–Wallis statistic (which is a non-parametric test for the equality of the mean return distributions across all five recommendation categories) 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, strongly 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 the 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 a positive (negative) return following hold, buy, and strong-buy recommendations or a negative (positive) return following sell and strong-sell recommendations.

[Please insert Figure 3 here]

Starting with the raw returns (Figure 3a), out of 340 technical buy recommendations, 250 turn out to be correct, while only 90 are incorrect. The 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 correct and incorrect strong-sell recommendations are nearly identical. Moving to risk-adjusted returns (Figure 3b), the number of correct technical recommendations is substantially larger than the number of incorrect ones across all the categories, including sell (145 versus 118) and strong sell (46 versus 26). The corresponding fundamental figures are 148 versus 140 and 34 versus 30, respectively. A simple sign test confirms the superiority of technical analysis. The null hypothesis of an equal number of correct and incorrect technical recommendations is significantly rejected ($p < 0.01$) for all the 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 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 19.7% (technical) versus 18.3% (fundamental). Similarly, the average return of incorrect buy recommendations is –13.7 (technical) versus –14.6 (fundamental). Aggregating the figures, buy recommendations are followed by an average return of (250 × 19.7% – 90 × 13.7%) / 340 = 10.86% (technical) versus (242 × 18.3% – 102 × 14.6%) / 344 = 8.59% (fundamental). Similarly, the performance figures favor technical recommendations among all the recommendation categories, based on the raw and risk-adjusted returns. The advantage is apparent in two dimensions: the number of correct recommendations and the quality of recommendations manifested through higher gains following correct recommendations and lower losses following incorrect ones.

4.1 Cross-section analysis

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

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

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 the return volatility measured by 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 the 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 earnings per share during the past two quarters.

Table 3 reports the regression evidence. We perform sixteen distinct tests. The dependent variable in most of the tests (unless otherwise noted) is the six-month return following the broadcast. Test 1 excludes all the control variables. Here, consistent with the previous analyses, the fundamental recommendations' (REC_i) coefficient is insignificant, while its technical counterpart is significantly positive (t = 6.82). Test 2 considers the past six-month return as a control variable. While the past return enters significantly, the technical recommendations' coefficient is still significantly positive (t = 5.52). Likewise, unreported regressions confirm that the 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 technicians to deliver reasonably robust predictions.

Tests 3 also controls for size, book-to-market, 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 average market capitalization of 39 billion dollars, and medium book-to-market firms belonging to the 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 the additional control variables are insignificant.

[Please insert Table 3 here]

Test 4 further accounts for the past returns over various periods, change in volume and volatility in the last three months and earnings surprises, as well as controlling for the potential immediate impact of the recommendation broadcast on the stock return and trading volume. Again, the fundamental recommendations do not display economic or statistical significance, whereas the 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 the 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 the stock price and trading volume, the predictive ability of technical recommendations persists long afterwards (see also the evolution of investment payoffs displayed in Figure 1, which, conservatively, excludes the broadcast day in accumulating payoffs).

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

Our sample consists of a relatively homogeneous 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 a superior forecast ability due to the self-selection process. Presumably, those females who have superb abilities as analysts pursue a career in a male-dominated industry. Our sample contains about 90% male analysts among the fundamentalists and technicians across all the asset classes (see Table 1). Thus, gender does not seem to represent a potential source of 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 = 5.13 for males and 3.47 for females). While the coefficient corresponding to female analysts is slightly larger (0.029 versus 0.024), the gender effects are altogether insignificant. In sum, the success of technical recommendations in predicting returns on individual stocks is not captured by the analyst's gender effect. Moreover, female technicians or fundamental analysts do not outperform their male counterparts.

While the dependent variable in Tests 1 through 7 is the stock return (raw or risk-adjusted) over six months following the recommendation broadcast, we also examine one-, three, nine- and twelve-month investment returns following the broadcasts. Tests 8 through 11 report the empirical evidence. For all the investment horizons, the fundamental recommendations' coefficients are indistinguishable from zero, while their technical counterparts are positively significant.

The remainder tests in Table 3 display the robustness of the results focusing on the six-month returns. Test 12 excludes the hold category to avoid potential misclassification errors.

Indeed, the difference between buy and sell recommendations is distinctive from the difference between hold and buy or hold and sell recommendations. Similarly, the difference between buy and sell recommendations is distinctive from the difference between buy and strong-buy and between sell and strong-sell recommendations.

Test 13 focuses on the all-buy and all-sell categories. As noted earlier, the all-buy category is composed of both buy and strong-buy recommendations, while the all-sell category 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 = 5.73 and t = 4.14, 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 14 and 15 examine the sensitivity of the results to the presence of outliers. The dependent variable in Test 14 is the six-month return winsorised at 2.5%. In Test 15, 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 = 5.90 and t = 3.44, respectively), suggesting that the stock-picking skills of technical analysts are not attributable to outliers.

Finally, a few programs feature a single, either fundamental or technical, recommendation with no comparison. While all the reported tests exclude such programs, Test 16 accounts for single-recommendation shows. The overall evidence remains unchanged.

To summarize, the cross-section regressions confirm the strong predictive ability of technical recommendations, as demonstrated in Figure 1. That predictive ability is uncaptured by the firm's size, book-to-market, volatility, volume, and past stock trends, as well as by common risk factors, the analyst's gender, and the apparent direct impact of recommendation broadcasts on stock prices. The results are also robust to the presence of outliers as well as potential classification errors. Fundamental recommendations, in contrast, do not exhibit a clear and consistent relation with the subsequent returns.

4.2 Examining the industry and style effects

Boni and Womack (2006) argue that the economic value of financial analysts relates to their status as industry specialists. To explore the potential effects of industry affiliation and firm attributes on recommendations, we ran the following 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 returns) and REC_i describes the recommendation category (1 – strong sell, 5 – strong buy). We consider two specifications. In one, $FIRM_{ij}$ (j = 1,2,…,6) are dummies for six 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 the construction and the wholesale trade and administration sectors, for which we record fewer than ten observations, are merged with 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 the firm's size, the book-to-market ratio, the volatility or the past return.

[Please insert Table 4 here]

Table 4 reports the results. Starting with the fundamental analysis, the recommendations do predict the future returns in the services industry. The mining coefficient is negatively significant, while all the other recommendation coefficients are generally insignificant. Moving to the technical front, excluding the mining industry, the analyst recommendations produce robust predictions based on the raw and risk-adjusted returns. The failure to predict the mining stock returns is consistent with the prominent inability of both technicians 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 the size, book-to-market ratio, volatility, and past return groups of the fundamental recommendations are, for the most part, insignificant. This is consistent with the notion that fundamental recommendations display low power in predicting future returns across all the equity styles. In contrast, all the coefficients corresponding to the technical recommendations are highly significantly positive.

5. Examining recommendations 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). In addition, as noted in the introduction, technicians can filter out insider buying and selling activities from the charts. If so, the essential hypothesis is that the success in predicting individual stock returns does not translate into robust predictions of broader asset returns.

The empirical evidence provides support for that hypothesis. In particular, Figure 4 presents the average returns on various asset classes for each school of thought. The left (right) plots feature fundamental (technical) recommendations. The asset classes include the S&P 500 index (Figure 4a), equity sectors and non-U.S. equity indexes (Figure 4b), U.S. bonds (Figure 4c), commodities (Figure 4d) and the U.S. dollar (Figure 4e). Further details of the asset classes are provided in Appendix C. The five curves in each plot depict the average returns over one, three, six, nine, and twelve months following the recommendation broadcast.

[Please insert Figure 4 here]

Briefly, Plots 4a through 4d show that both technicians and fundamental analysts are unable to predict the S&P 500 index, equity sectors and non-U.S. equity indexes, 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 the investment horizon of one year.

Likewise, Figure 5 presents the cumulative returns relative to the 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 for the S&P 500 index, equity sectors and non-U.S. equity indexes, bonds, and commodities. In contrast, both investment approaches 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. To start with, only 21 dual recommendations on exchange rates were recorded. Moreover, past work supports the notion that the transparent monetary policies of central banks to keep interest rates low and improve liquidity could enhance the ability to predict future rates. 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 similar predictive patterns among technicians and fundamental analysts even when the two schools of thought implement very different toolkits, typically leading to very different predictions.

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

Table 6 reports summary statistics similar to those exhibited in Table 2 but focusing on the broader asset classes. Staring with the market index, consistent with Figure 5a, there is no clear association between recommendations and subsequent returns. The 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 is in the wrong direction as the mean returns corresponding to sell recommendations are higher than those corresponding to buy recommendations.

[Please insert Table 6 here]

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

The apparent success in predicting individual stock returns is the exception rather the rule. In all the other asset classes, excluding the U.S. dollar, both technicians and fundamental analysts 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.

6. Conclusion

This study employs a novel database from a TV broadcast in a head-to-head confrontation of the performance of fundamental analysts versus technicians to assess their economic value. The data are composed of fundamental and technical simultaneous recommendations for the same underlying assets with the same investment horizon. The unique setup of the broadcast, featuring synchronized dual recommendations, a great variety of asset classes and the presence of leading professionals, offers an ideal laboratory in which to assess the value of financial analysis. Ultimately, both technicians and fundamental analysts are exposed to the same public information and their recommendations could differ due to the distinct toolkits applied.

The simultaneous broadcast equates analyst exposure to herding, eliminates time gap biases such as cross-herding among analysts, and allows one to control for the immediate short-term effect of the broadcast itself. The high profile of the participating analysts levels the playing field, thereby mitigating the 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 the 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, excluding the

U.S. dollar. Surprisingly, the technicians exhibit a 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 a start, trading individual stocks based on technical recommendations yields large payoffs even after accounting for reasonable transaction costs. Moreover, such stock-picking ability is unaffected by controlling for common risk factors, the firm's characteristics, including past returns, industry effects, the analyst's gender, the potential immediate impact of the broadcast, and outliers.

However, the predictive ability of technicians characterizes individual stocks only (and the U.S. dollar). In contrast, returns on more general asset classes, including the market indexes, equity sectors and non-U.S. equity indexes, bonds, and commodities, are unpredictable. Such differential results support the notion that the predictive ability of technicians relies on the possession of proprietary investment toolkits. Considering the nature of technical analysis, one appealing explanation is that such toolkits enable their users to extract private information from informed buying and selling activities, which are more applicable to individual stocks and less so to broader asset classes. Of course, arbitrage capital is invested more in general assets and indexes, thereby eliminating abnormal profits, if there are any, from trading 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 the first simultaneous fundamental–technical comparison was broadcasted) through December, 31 2014. The exact list of assets is provided in Appendix C. 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 the frequencies of fundamental and technical recommendations across categories are not significantly different

	Fundamental / Technical	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 equity sectors and 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 the return and the recommendation category. The investment horizons are one, three, six, nine and twelve months following the recommendations. Panel A (B) considers the raw (risk-adjusted) average returns, with risk adjustment pertaining to the Fama–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 mean return. The Mann–Whitney null hypothesis asserts that all-buy and all-sell recommendations exhibit the same return distribution.

		Fundamental Recommendations									Technical Recommendations								
Period (Months)		**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	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	(0.33)	-38.3	-54.7	-33.9	-27.1	-36.0	**(0.02)**	-54.7	-36.0	**(0.01)**
Three	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		0.7	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	7.01	109.9	92.5	1.19	51.4	102.0	92.5	109.9	76.1	8.17	102.0	109.9	**2.35**
	Min.	-46.0	-64.4	-39.5	-63.8	-46.3	(0.14)	-64.4	-63.8	(0.12)	-64.4	-63.8	-40.9	-39.9	-46.3	(0.09)	-64.4	-46.3	**(0.01)**
Six	Mean	8.3	10.7	10.5	8.6	16.1		10.3	10.6		3.6	7.2	11.8	10.9	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	0.6	1.5		1.0	1.0	
	Max.	134.0	166.8	199.4	119.1	216.0	**10.27**	166.8	216.0	1.04	119.1	130.6	216.0	134.0	166.8	**27.30**	130.6	166.8	**4.50**
	Min.	-54.2	-77.1	-53.6	-51.8	-53.1	**(0.04)**	-77.1	-53.1	(0.15)	-53.6	-51.8	-54.2	-77.1	-57.9	**(0.00)**	-53.6	-77.1	**(0.00)**
Nine	Mean	11.3	18.3	18.5	13.7	21.7		17.0	15.8		11.0	13.9	16.8	16.5	24.7		13.3	19.0	
	Std dev.	48.2	35.9	35.9	29.3	34.3		38.5	30.9		41.4	34.2	37.6	29.8	37.1		35.9	32.4	
	Skewness	1.8	2.2	2.4	1.1	1.9		2.0	1.4		1.7	2.0	2.5	1.5	1.9		1.8	1.7	
	Max.	238.8	242.4	258.8	199.2	217.9	8.16	242.4	217.9	0.47	199.2	242.4	258.8	238.8	236.3	**14.96**	242.4	238.8	**3.24**
	Min.	-55.5	-54.3	-58.6	-58.7	-68.7	(0.09)	-55.5	-68.7	(0.32)	-68.7	-58.7	-55.9	-58.6	-40.3	**(0.00)**	-68.7	-58.6	**(0.00)**
Twelve	Mean	7.5	23.4	26.5	20.3	25.4		20.4	21.7		16.7	19.0	21.1	22.4	30.1		18.5	24.9	
	Std dev.	56.4	41.3	40.5	35.4	32.6		44.9	34.7		47.1	40.9	39.7	36.7	38.5		42.4	37.4	
	Skewness	2.8	1.4	1.8	1.2	0.4		1.8	1.0		1.8	1.5	1.6	1.8	1.3		1.6	1.6	
	Max.	315.8	255.5	254.7	234.3	148.2	**18.77**	315.8	234.3	1.41	234.3	255.5	254.7	315.8	232.8	**14.89**	255.5	315.8	**3.26**
	Min.	-71.6	-62.0	-72.0	-69.6	-72.0	**(0.00)**	-71.6	-72.0	(0.08)	-59.2	-72.0	-71.6	-56.1	-72.0	**(0.00)**	-72.0	-72.0	**(0.00)**
								B. Risk-adjusted returns											
One	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	2.72	90.6	52.2	0.73	34.1	31.7	52.2	74.6	90.6	**14.88**	34.1	90.6	**3.34**
	Min.	-35.5	-40.6	-24.7	-46.9	-31.5	(0.61)	-40.6	-46.9	(0.23)	-40.6	-46.9	-35.5	-24.7	-38.3	**(0.00)**	-46.9	-38.3	**(0.00)**
Three	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	5.82	92.2	73.6	1.18	44.4	82.1	73.6	92.2	64.3	**12.95**	82.1	92.2	**3.02**
	Min.	-41.3	-62.3	-38.0	-59.7	-50.1	(0.21)	-62.3	-59.7	(0.12)	-62.3	-59.7	-34.1	-41.3	-50.1	**(0.01)**	-62.3	-50.1	**(0.00)**
Six	Mean	-1.3	0.8	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	20.6	
	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	7.80	143.0	170.1	1.15	76.2	104.1	170.1	110.5	143.0	**23.34**	104.1	143.0	**4.29**
	Min.	-54.9	-76.2	-57.5	-55.9	-56.9	(0.10)	-76.2	-56.9	(0.12)	-57.5	-55.9	-54.9	-76.2	-61.4	**(0.00)**	-57.5	-76.2	**(0.00)**
Nine	Mean	-2.9	2.8	3.8	0.2	4.9		1.8	1.5		-3.5	-0.6	2.7	2.4	7.4		-1.2	3.9	
	Std dev.	39.2	28.4	28.2	23.6	26.2		30.7	24.4		32.8	27.1	29.6	23.9	29.2		28.4	25.8	
	Skewness	1.5	2.1	1.7	0.7	1.5		1.8	1.0		1.4	1.6	1.7	1.2	1.8		1.5	1.5	
	Max.	172.0	182.5	160.0	135.1	152.3	6.79	182.5	152.3	0.86	135.1	170.9	160.0	172.0	182.5	**16.64**	170.9	182.5	**3.66**
	Min.	-61.6	-57.9	-61.5	-64.3	-71.9	(0.15)	-61.6	-71.9	(0.20)	-71.9	-64.3	-61.6	-61.5	-52.4	**(0.00)**	-71.9	-61.5	**(0.00)**
Twelve	Mean	-9.7	2.4	5.7	1.9	4.6		0.1	2.6		-2.2	-0.2	2.2	2.5	8.0		-0.6	4.3	
	Std dev.	43.2	30.9	29.0	27.5	25.8		33.9	27.1		36.3	30.8	29.0	28.2	29.5		32.1	28.7	
	Skewness	2.2	1.1	1.2	0.8	0.1		1.4	0.7		1.2	1.1	0.8	1.4	0.9		1.2	1.2	
	Max.	205.8	158.0	132.9	142.9	84.5	**19.57**	205.8	142.9	2.01	142.9	158.0	132.9	205.8	151.2	**11.87**	158.0	205.8	**2.86**
	Min.	-76.3	-67.7	-72.6	-73.5	-76.1	**(0.00)**	-76.3	-76.1	(0.02)	-65.9	-76.1	-76.3	-64.7	-72.6	**(0.02)**	-76.1	-72.6	**(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 the return volatility measured by the 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 the previous-year figures; $RECIMPACT_i^{j=1,2}$ 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 earnings 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 by analysts. One and two asterisks indicate a significance level of 5% and 1%, respectively.

			Recommendation		Firm Characteristics				Potential Explanation									
									Past Return			ΔVolume	ΔVolatility	Rec. Impact		Surprise		
Dependent 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															1.08
		(2.75**)	(1.04)															
	1b.	0.017		0.027														46.5
		(1.10)		(6.82**)														
	2a.	0.078	0.006						0.052									2.6
		(2.93**)	(0.87)						(1.71)									
	2b.	0.019		0.024					0.043									19.1
Six-month		(1.07)		(5.52**)					(2.39*)									
returns	3a.	-0.009	0.008		-0.005	-0.000	1.155	0.007	0.038									5.3
		(-0.08)	(1.15)		(-0.43)	(-1.45)	(0.62)	(0.77)	(1.21)									
	3b	-0.040		0.025	-0.005	0.000	1.129	0.005	0.029									16.7
		(-0.30)		(5.54**)	(-0.46)	(-1.50)	(0.84)	(0.62)	(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	0.956	-0.081	0.010	-0.022	14.1
		(1.23)	(0.58)		(-0.36)	(-1.82)	(1.22)	(-0.29)	(0.15)	(-0.34)	(0.57)	(0.91)	(0.39)	(4.76**)	(-3.83**)	(0.83)	(-1.73)	
	4b.	0.103		0.020	-0.003	0.000	2.576	-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.	-0.034	0.007		-0.006	-0.000	0.292	0.004	0.025									10.1
		(-0.32)	(1.11)		(-0.54)	(-1.97*)	(0.17)	(0.52)	(0.97)									
Six-month	5b.	-0.062		0.021	-0.005	-0.000	0.253	0.003	0.017									48.2
returns adjusted		(-0.44)		(5.67**)	(-0.64)	(-2.09*)	(0.22)	(0.35)	(0.92)									
to	6a.	0.086	0.004		-0.003	0.000	1.842	-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)	(-2.10*)	(1.00)	(-0.58)	(-0.43)	(-0.30)	(0.87)	(1.09)	(0.61)	(4.08**)	(-4.40**)	(1.04)	(-1.81)	
	6b.	0.052		0.017	-0.002	0.000	1.919	-0.006	-0.017	-0.055	0.054	0.047	0.036	0.768	-0.069	0.011	-0.018	24.2
		(0.36)		(3.53**)	(-0.30)	(-2.22*)	(1.35)	(-0.70)	(-0.48)	(-0.56)	(0.66)	(1.14)	(0.55)	(4.96**)	(-3.20**)	(1.17)	(-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.	-0.002	0.010	0.004				-0.005	0.000	1.120	0.006	1.97	4.7
		(-0.01)	(1.32)	(0.47)				(-0.42)	(-1.46)	(0.60)	(0.73)	(p =0.16)	
	7b.	-0.039			0.024	0.029	-0.004	0.000	1.098	0.005	0.029	0.25	14.4
		(-0.29)			(5.13**)	(3.47**)	(-0.45)	(-1.51)	(0.80)	(0.61)	(1.22)	(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)	(0.48)				(-1.65)	(-0.36)	(-0.24)	(1.06)	(0.55)		
	8b.	0.007			0.006		-0.005	0.000	-0.121	0.002	0.004		5.7
		(0.21)			(2.40*)		(-1.48)	(-0.28)	(-0.29)	(1.00)	(0.31)		
3-month returns	9a.	0.045	0.007				-0.010	0.000	-0.172	0.006	0.005		0.7
		(0.54)	(0.99)				(-1.43)	(-1.66)	(-0.16)	(0.99)	(0.20)		
	9b.	0.044			0.009		-0.010	0.000	-0.250	0.006	0.002		3.4
		(0.56)			(2.24*)		(-1.72)	(-1.38)	(-0.26)	(1.24)	(0.19)		
9-month returns	10a.	-0.050	0.009				0.010	0.000	5.435	-0.002	0.020		7.7
		(-0.37)	(0.96)				(0.90)	(-0.22)	(2.94**)	(-0.21)	(0.42)		
	10b.	-0.079			0.024		0.011	0.000	5.394	-0.003	0.011		17.3
		(-0.47)			(3.32**)		(0.87)	(-0.09)	(3.51**)	(-0.35)	(0.29)		
12-month returns	11a.	-0.253	0.017				0.025	0.000	5.842	0.002	0.048		7.0
		(-1.78)	(1.34)				(1.94)	(0.80)	(4.06**)	(0.15)	(1.04)		
	11b.	-0.267			0.027		0.026	0.000	5.683	0.000	0.040		7.2
		(-1.39)			(3.83**)		(1.79)	(0.66)	(3.50**)	(-0.00)	(0.86)		
6-month returns, 4 categories (no hold)	12a.	-0.008	0.008				0.001	0.000	1.149	0.003	0.034		1.3
		(-0.07)	(1.05)				(0.08)	(-0.45)	(0.56)	(0.33)	(0.92)		
	12b.	-0.025			0.025		-0.006	0.000	0.138	0.006	0.043		11.1
		(-0.17)			(5.73**)		(-0.74)	(-1.15)	(0.14)	(0.76)	(2.20*)		
6-month returns, 2 categories (buy, sell)	13a.	0.006	0.003				0.001	0.000	1.037	0.003	0.036		1.1
		(0.05)	(0.20)				(0.12)	(-0.31)	(0.51)	(0.34)	(0.96)		
	13b.	-0.035			0.054		-0.006	0.000	0.091	0.006	0.046		9.4
		(-0.22)			(4.14**)		(-0.75)	(-1.17)	(0.09)	(0.81)	(2.32*)		
6-month returns, winsorising at 2.5%	14a.	-0.018	0.007				-0.003	0.000	0.105	0.007	0.053		8.0
		(-0.18)	(1.30)				(-0.33)	(-1.60)	(0.09)	(0.93)	(1.94)		
	14b.	-0.051			0.024		-0.003	0.000	0.099	0.006	0.044		26.9
		(-0.40)			(5.90**)		(-0.41)	(-1.97*)	(0.11)	(0.77)	(2.38*)		
6-month returns, quantile regression ($\tau = 0.5$)	15a.	-0.172	0.010				-0.013	0.000	-1.893	0.024	0.076		
		(-2.17*)	(1.78)				(-1.57)	(-0.13)	(-1.36)	(3.77**)	(4.90**)		
	15b.	-0.126			0.018		-0.009	0.000	-1.805	0.018	0.062		
		(-1.57)			(3.44**)		(-1.23)	(-0.11)	(-1.36)	(2.98**)	(3.90**)		
6-month returns, including single recommendations (no comparison)	16a.	-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)		
	16b.	-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)		

Table 4. Industry and style effects

The table reports the results of the following regression:

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

where R_i is the stock return or return adjusted for the 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: six industry dummies in Panel A and three dummies in Panel B corresponding to the bottom 30%, core 40% and top 30% of the firm's size, the book-to-market ratio, the volatility, or the past return from 2 to 12 months prior to the 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 by 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									
Fundamental	R	0.083	-0.037	0.007	0.013	-0.003	0.008	0.016	6.6
		(2.94**)	(-3.62**)	(0.89)	(1.61)	(-0.33)	(0.97)	(2.46*)	($p < 0.001$)
	R_{adj}	-0.010	-0.027	0.007	0.011	0.001	0.001	0.013	3.8
		(-0.44)	(-2.39*)	(0.97)	(1.51)	(0.15)	(0.10)	(2.18*)	($p = 0.002$)
Technical	R	0.017	-0.022	0.027	0.030	0.016	0.026	0.041	12.2
		(0.93)	(-1.40)	(5.02**)	(5.91**)	(1.97*)	(3.66**)	(5.24**)	($p < 0.001$)
	R_{adj}	-0.064	-0.015	0.023	0.024	0.016	0.016	0.035	7.4
		(-4.62**)	(-0.92)	(5.23**)	(5.37**)	(2.74**)	(2.63**)	(5.22**)	($p < 0.001$)

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	-0.012	0.017	-0.063	0.084	-0.008	0.017	-0.063	0.091	0.000	0.018	-0.062	0.092	-0.002	0.020	-0.060
	(2.66**)	(-0.51)	(1.09)	(-5.10**)	(2.71**)	(-0.34)	(1.06)	(-5.30**)	(3.34**)	(0.003)	(0.98)	(-4.53**)	(3.02**)	(-0.07)	(1.08)	(-4.29**)
Bottom					0.010	0.009	0.032	0.027	0.001	-0.004	0.029	0.020	0.013	0.011	0.035	0.030
					(1.45)	(1.49)	(7.03**)	(6.95**)	(0.09)	(-0.42)	(4.05**)	(3.57**)	(1.09)	(1.13)	(7.40**)	(7.64**)
Core	0.020	0.017	0.046	0.037	-0.001	0.001	0.020	0.018	0.016	0.012	0.035	0.028	0.006	0.007	0.028	0.024
	(2.35*)	(2.31*)	(5.86**)	(5.57**)	(-0.09)	(0.12)	(3.64**)	(4.48**)	(2.12*)	(1.88)	(5.85**)	(5.47**)	(1.01)	(1.27)	(6.07**)	(6.25**)
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
	(0.66)	(0.76)	(5.00**)	(4.93**)	(-0.09)	(-0.39)	(3.23**)	(2.92**)	(-0.53)	(-0.12)	(3.71**)	(4.97**)	(-0.11)	(-0.14)	(2.97**)	(3.03**)
F all equal					3.02	2.99	6.29	5.10	12.49	8.99	27.69	3.59	2.42	2.49	2.20	2.54
(p-value)					(0.05)	(0.05)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)	(0.09)	(0.08)	(0.11)	(0.08)
F bottom equal top	2.19	2.24	5.22	4.84	3.85	5.23	2.62	6.82	0.16	0.16	2.37	0.07	2.08	2.31	3.76	4.87
(p-value)	(0.14)	(0.13)	(0.02)	(0.03)	(0.05)	(0.02)	(0.11)	(0.01)	(0.69)	(0.69)	(0.12)	(0.78)	(0.15)	(0.13)	(0.05)	(0.03)

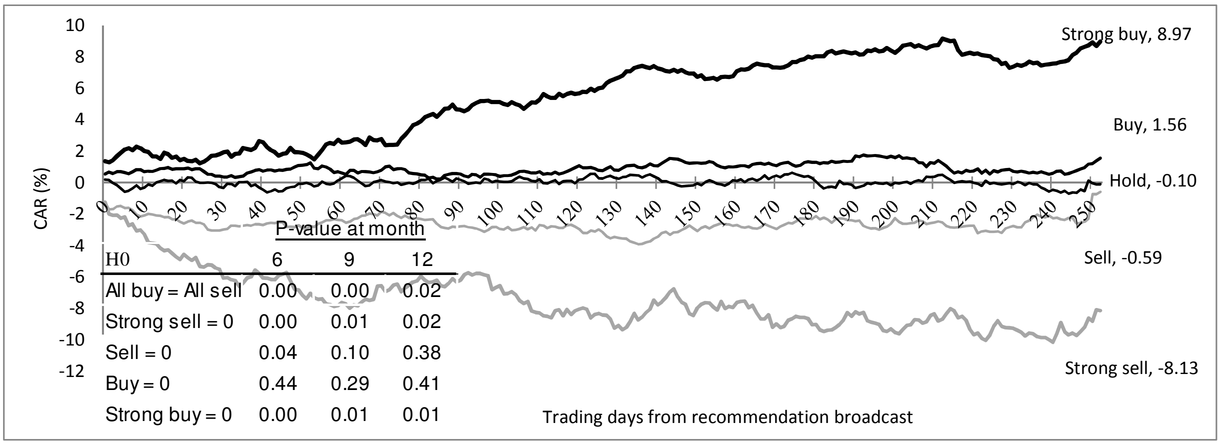
Table 5. Summary statistics of the average returns on broader asset classes
The table reports the summary statistics of the returns on various asset classes for each recommendation category over one, three, six, nine and twelve months following the recommendations broadcast. The asset classes are the S&P 500 index, equity sectors and non-U.S. equity indexes, U.S. bonds, commodities and the U.S. dollar. The Kruskal–Wallis test's null hypothesis asserts that the investment mean returns based on the five categories have the same distribution. The Mann–Whitney test's null hypothesis asserts that all-buy and all-sell recommendations have the same distribution. When no statistic exists, it is denoted as "not applicable" (na).

		Fundamental Recommendations							Technical Recommendations						
Period		**Strong Sell**	**Sell**	**Hold**	**Buy**	**Strong Buy**	**Kruskal–Wallis**	**Mann–Whitney**	**Strong Sell**	**Sell**	**Hold**	**Buy**	**Strong Buy**	**Kruskal–Wallis**	**Mann–Whitney**
						A. The U.S. S&P 500 index									
1 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)**
3 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)
6 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)
9 months	Mean	16.3	10.9	11.1	9.4	10.6			13.2	11.1	11.5	9.2	13.1		
	Std dev.	1.1	4.0	4.4	7.2	4.2			4.3	4.5	4.5	6.5	3.9		
	Skewness	na	0.9	0.1	-0.4	-0.3			na	1.1	-1.5	-0.3	0.5		
	Max.	17.4	21.5	22.5	22.6	16.7	3.87	0.73	17.5	22.6	17.6	22.2	20.9	6.92	0.63
	Min.	15.2	5.6	0.7	-5.0	3.8	(0.42)	(0.23)	8.9	5.6	-4.4	-5.0	7.1	(0.14)	(0.47)
12 months	Mean	22.6	13.6	12.0	14.9	17.1			19.4	13.9	14.5	13.1	15.3		
	Std dev.	2.1	6.0	7.9	8.0	4.6			5.2	7.0	4.4	8.0	9.6		
	Skewness	na	0.5	-0.3	-0.5	0.2			na	0.4	-1.8	-0.2	-0.8		
	Max.	24.7	29.9	30.9	34.1	23.8	9.36	1.38	24.7	34.1	20.5	30.9	30.5	2.74	0.07
	Min.	20.5	-0.6	-2.7	-4.6	10.8	(0.05)	(0.08)	14.2	-2.7	-0.6	-2.7	-4.6	(0.60)	(0.43)
						B. Equity sectors and non-U.S. equity indexes									
1 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)
3 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)
6 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)
9 months	Mean	13.6	7.8	9.9	8.2	5.8			10.2	8.1	10.3	7.6	8.6		
	Std dev.	8.3	13.0	11.1	15.8	14.1			12.7	12.3	12.9	14.5	13.3		
	Skewness	1.2	-1.0	0.6	-0.5	0.1			-2.1	-0.9	0.7	-0.5	-0.4		
	Max.	32.2	45.7	50.9	51.8	37.3	2.29	0.26	33.0	37.3	51.8	45.7	40.1	1.24	0.73
	Min.	5.5	-38.3	-18.0	-34.8	-19.3	(0.68)	(0.40)	-38.3	-31.0	-23.6	-36.9	-26.3	(0.87)	(0.23)

		Fundamental Recommendations							Technical Recommendations						
Period		Strong Sell	Sell	Hold	Buy	Strong Buy	Kruskal–Wallis	Mann–Whitney	Strong Sell	Sell	Hold	Buy	Strong Buy	Kruskal–Wallis	Mann–Whitney
12 months	Mean	17.7	8.4	12.5	11.8	13.2			10.7	10.5	12.4	10.7	11.9		
	Std dev.	10.7	17.9	12.4	19.9	5.4			11.0	15.4	16.3	19.5	16.6		
	Skewness	0.5	-0.7	-0.1	-0.8	-0.5			-1.8	-0.6	0.0	-0.9	-2.3		
	Max.	36.1	66.2	53.1	59.0	20.5	4.53	1.14	31.0	44.8	59.0	66.2	36.2	0.95	0.65
	Min.	3.4	-54.2	-27.8	-47.8	3.8	(0.34)	(0.13)	-29.3	-30.9	-46.2	-54.2	-42.3	(0.92)	(0.26)
							C. Bonds								
1 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)
3 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)**
6 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)
9 months	Mean	5.6	2.4	2.8	2.2	2.5			3.0	3.5	2.5	1.4	3.4		
	Std dev.	0.0	3.9	2.9	4.0	2.5			3.3	1.7	2.4	5.0	3.4		
	Skewness	na	-0.7	0.5	-0.6	-1.1			na	-0.9	1.7	-0.2	-0.1		
	Max.	5.6	9.7	9.2	9.6	5.1	1.35	0.12	6.2	5.7	9.2	9.7	8.4	3.04	1.16
	Min.	5.6	-8.9	-2.0	-6.2	-0.9	(0.85)	(0.45)	-0.3	0.1	-0.6	-8.9	-1.0	(0.55)	(0.12)
12 months	Mean	2.5	2.6	5.5	2.6	2.7			4.9	4.0	4.8	1.2	3.4		
	Std dev.	0.0	3.5	3.2	3.3	1.9			3.5	1.8	3.2	3.8	1.8		
	Skewness	na	-2.0	0.0	-1.3	-1.5			na	0.4	0.4	-1.6	-1.5		
	Max.	2.5	8.3	10.1	6.2	4.4	3.03	0.48	8.3	7.6	10.1	6.2	5.3	5.39	1.69
	Min.	2.5	-9.1	0.9	-5.0	0.0	(0.55)	(0.32)	1.4	0.9	0.7	-9.1	0.0	(0.25)	(0.05)
							D. Commodities								
1 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)
3 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)
6 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)
9 months	Mean	-10.9	-12.0	-14.3	-9.8	-12.9			-10.4	-11.9	-12.4	-13.4	-8.7		
	Std dev.	13.3	15.4	18.1	16.3	8.9			14.1	16.3	15.5	17.7	6.5		
	Skewness	-1.6	-1.0	-0.7	-1.8	0.4			-1.2	-1.0	-1.5	-1.1	-1.4		
	Max.	2.7	18.7	23.8	10.1	-2.0	2.31	0.80	10.1	18.7	2.7	23.8	-2.0	0.90	0.84
	Min.	-42.6	-55.7	-56.0	-62.4	-22.5	(0.68)	(0.21)	-41.9	-55.7	-55.6	-62.4	-22.5	(0.92)	(0.21)
12 months	Mean	-11.9	-12.3	-14.1	-10.0	-11.1			-10.6	-11.4	-13.6	-13.7	-8.4		
	Std dev.	14.2	15.9	16.3	15.1	6.8			16.2	16.8	13.1	14.8	5.1		
	Skewness	-2.3	-1.2	-1.0	-0.6	0.7			-2.0	-1.2	-0.9	-0.3	-0.5		
	Max.	3.0	20.4	13.0	11.6	-1.2	1.17	0.57	13.6	20.4	3.8	13.0	-1.2	1.71	0.81
	Min.	-57.5	-56.7	-56.4	-46.6	-17.4	(0.88)	(0.29)	-57.5	-56.7	-46.6	-44.1	-16.2	(0.79)	(0.21)

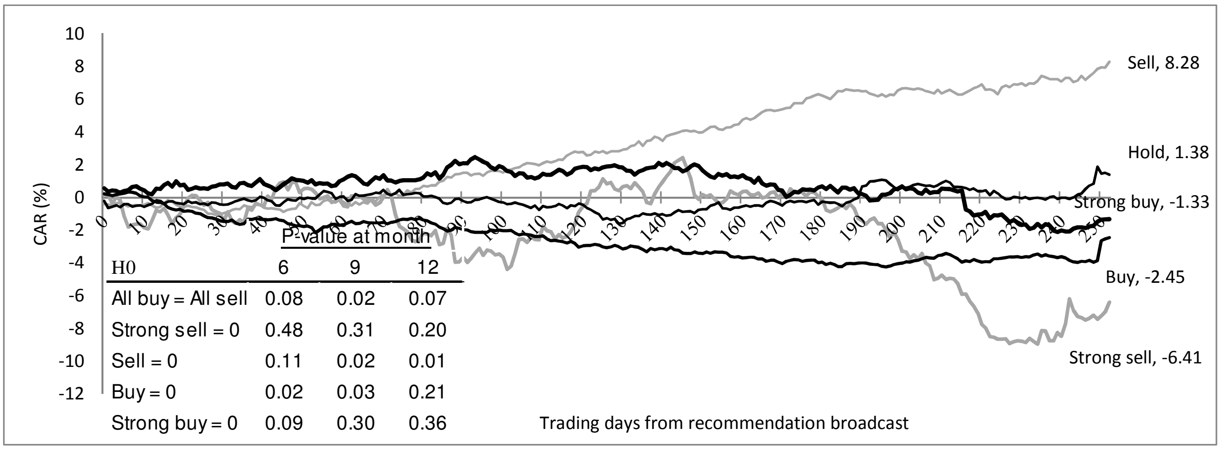
		Fundamental Recommendations							Technical Recommendations						
Period		**Strong Sell**	**Sell**	**Hold**	**Buy**	**Strong Buy**	**Kruskal–Wallis**	**Mann–Whitney**	**Strong Sell**	**Sell**	**Hold**	**Buy**	**Strong Buy**	**Kruskal–Wallis**	**Mann–Whitney**
							E. The U.S. dollar								
1 month	Mean	-3.3	-1.5	1.9	1.4	3.4			-2.5	-0.2	0.6	0.9	2.8		
	Std dev.	0.0	1.1	1.6	1.8	0.6			0.0	2.7	2.4	2.0	0.0		
	Skewness	na	-0.5	1.0	-0.7	na			na	1.1	1.7	-0.7	na		
	Max.	-3.3	-0.1	4.0	3.9	4.0	**11.89**	**2.85**	-2.5	4.0	3.9	4.0	2.8	3.28	1.33
	Min.	-3.3	-3.2	0.2	-2.1	2.8	**(0.02)**	**(0.00)**	-2.5	-3.2	-1.2	-3.3	2.8	(0.51)	(0.09)
3 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)**
6 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)**
9 months	Mean	-14.7	-15.3	8.0	9.9	11.5			-14.3	-11.5	-0.5	6.3	16.1		
	Std dev.	0.0	2.3	4.2	8.0	4.6			0.0	8.0	14.4	10.4	0.0		
	Skewness	na	0.7	-1.7	-0.7	na			na	1.8	0.2	-1.0	na		
	Max.	-14.7	-11.3	11.0	19.5	16.1	**13.84**	**3.49**	-14.3	2.1	17.6	19.5	16.1	7.62	**2.71**
	Min.	-14.7	-17.7	2.1	-4.2	7.0	**(0.01)**	**(0.00)**	-14.3	-17.7	-17.7	-14.7	16.1	(0.11)	**(0.00)**
12 months	Mean	-17.0	-17.0	5.3	10.8	19.6			-14.2	-8.5	-0.3	2.8	19.6		
	Std dev.	0.0	3.0	0.0	7.8	0.0			0.0	9.9	14.2	15.5	0.0		
	Skewness	na	-0.6	na	-1.2	na			na	1.6	-0.3	-0.7	na		
	Max.	-17.0	-13.6	5.3	18.3	19.6	**11.17**	**3.10**	-14.2	5.3	16.5	18.3	19.6	3.58	1.36
	Min.	-17.0	-21.8	5.3	-3.2	19.6	**(0.03)**	**(0.00)**	-14.2	-17.2	-18.3	-21.8	19.6	(0.47)	(0.09)

1a. CARs for technical recommendations



H0	P-value at month 6	9	12
All buy = All sell	0.00	0.00	0.02
Strong sell = 0	0.00	0.01	0.02
Sell = 0	0.04	0.10	0.38
Buy = 0	0.44	0.29	0.41
Strong buy = 0	0.00	0.01	0.01

1b. CARs for fundamental recommendations



H0	P-value at month 6	9	12
All buy = All sell	0.08	0.02	0.07
Strong sell = 0	0.48	0.31	0.20
Sell = 0	0.11	0.02	0.01
Buy = 0	0.02	0.03	0.21
Strong buy = 0	0.09	0.30	0.36

1c. Payoffs for spread portfolios

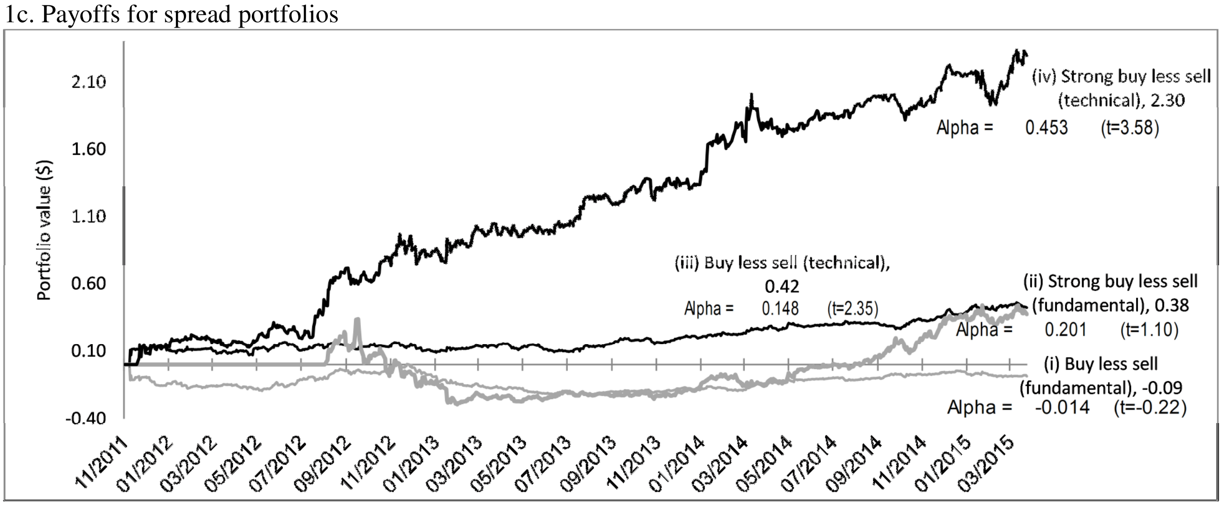
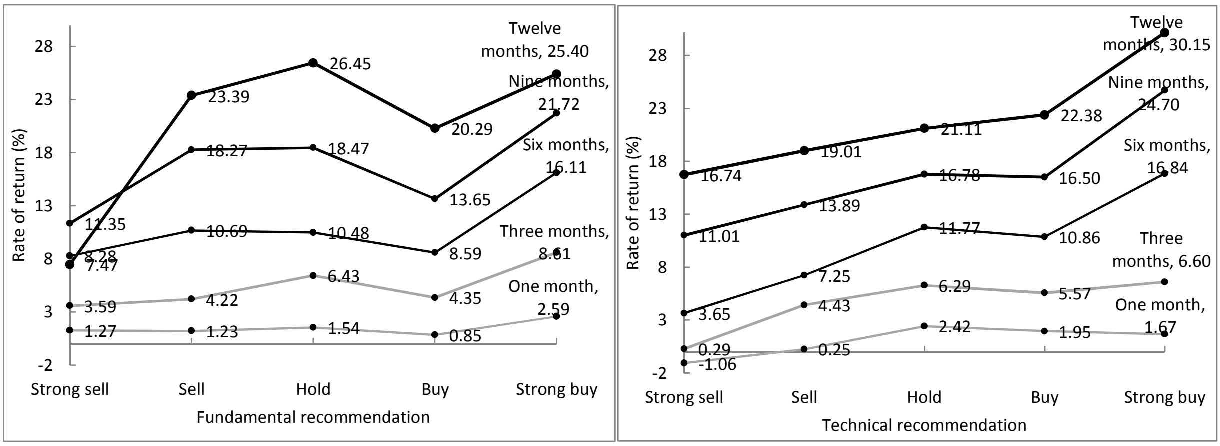


Figure 1. Cumulative abnormal returns (CARs) and portfolio payoffs

The top two panels depict the CARs for the technical and fundamental recommendations, starting with the recommendation broadcast (day zero) and ending twelve months afterwards. The *p*-values in the first test in each panel on the left-hand side correspond to Mann–Whitney–Wilcoxon statistics for the null hypothesis asserting that the CARs at six, nine or twelve months corresponding to buy and strong buy are not significantly different from those corresponding to sell and strong sell. The other tests are Wilcoxon signed-rank tests for the null hypothesis asserting that the CARs at six, nine or twelve months are indistinguishable from zero. The bottom panel presents the 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 the portfolio's excess return on the market excess return.

2a. Raw returns



2b. Adjusted returns

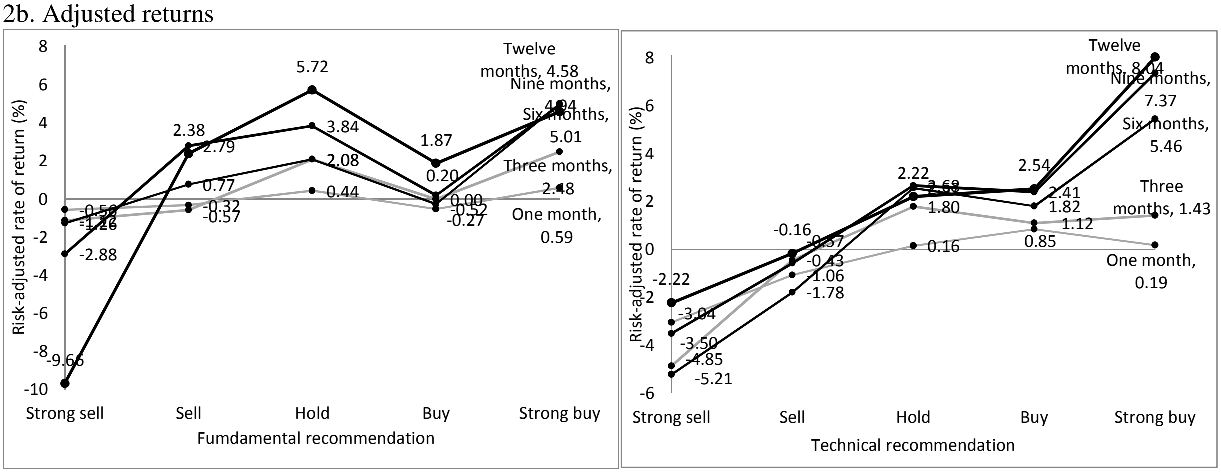
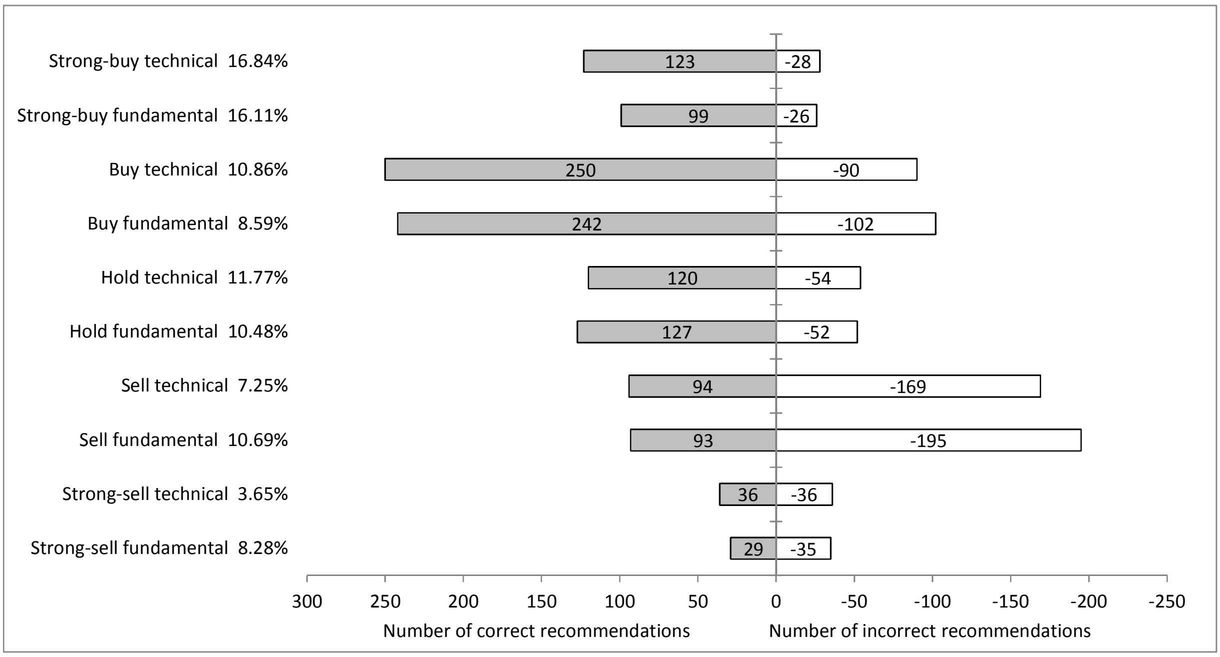


Figure 2. Average stock return per recommendation category for various investment horizons

The figure depicts the average returns on stocks for the strong-sell, sell, hold, buy and strong-buy categories. The five curves in each diagram exhibit average returns over one, three, six, nine and twelve months following the recommendation's broadcast. The left (right) figures pertain to fundamental (technical) analysis. The top figures exhibit the raw returns, while the bottom figures display the returns adjusted for the three Fama–French and momentum factors.

3a. Raw returns



3b. Risk-adjusted returns

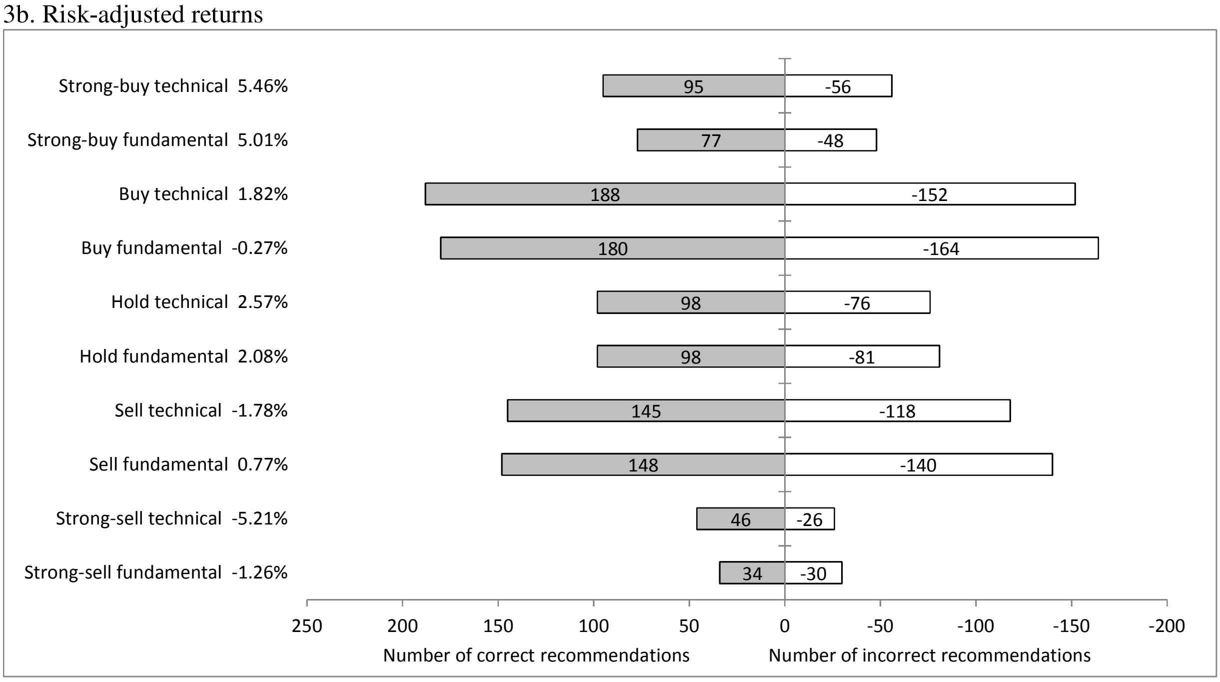
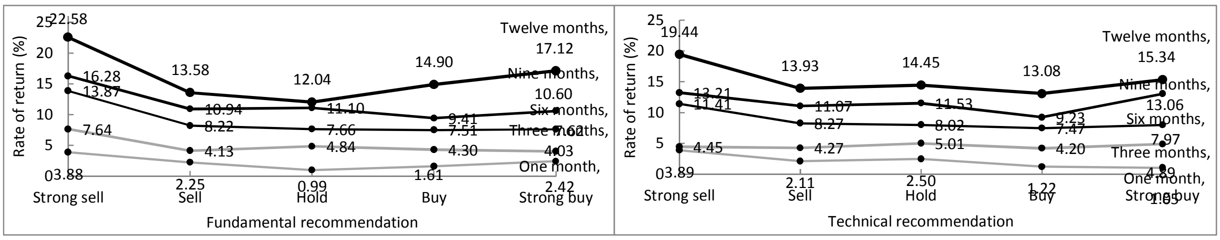


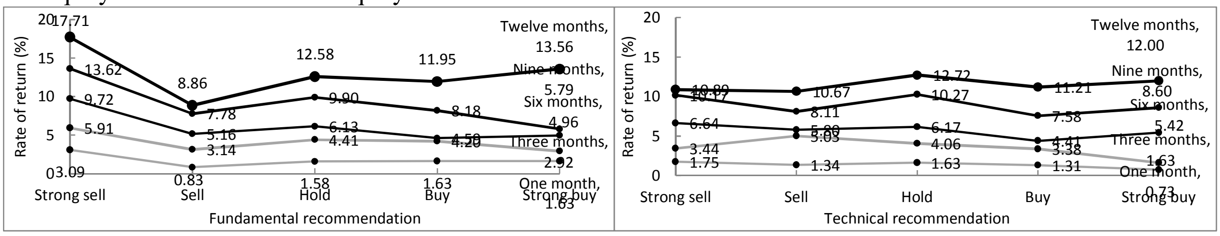
Figure 3. The number of correct and incorrect stock recommendations

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 a positive (negative) return following hold, buy and strong-buy recommendations or a 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. The top figure exhibits the raw returns, while the bottom figure displays the returns adjusted for the three Fama–French and momentum factors.

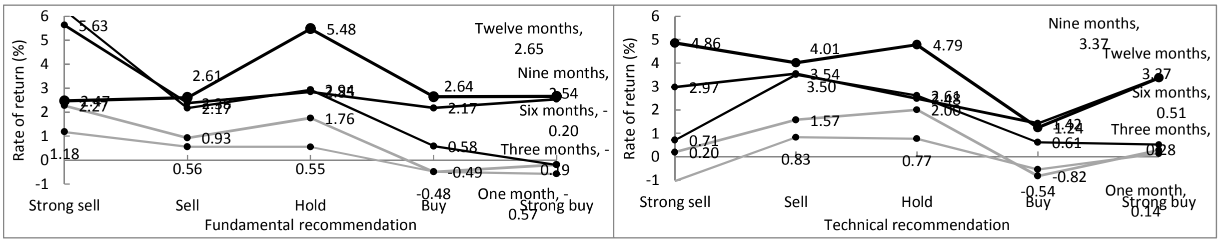
4a. S&P 500



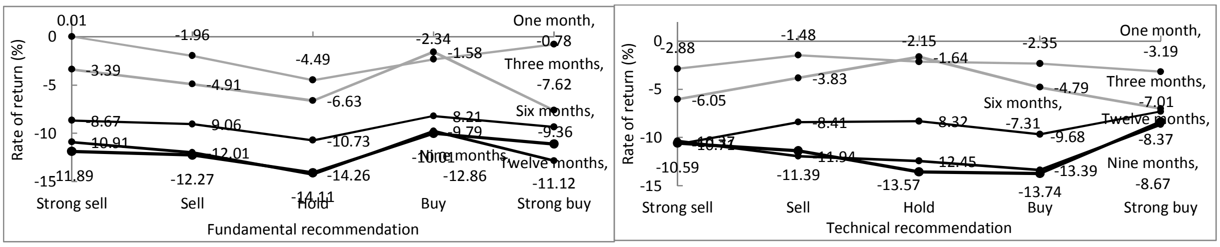
4b. Equity sectors and non-U.S. equity indexes



4c. U.S. bonds



4d. Commodities



4e. U.S. dollar

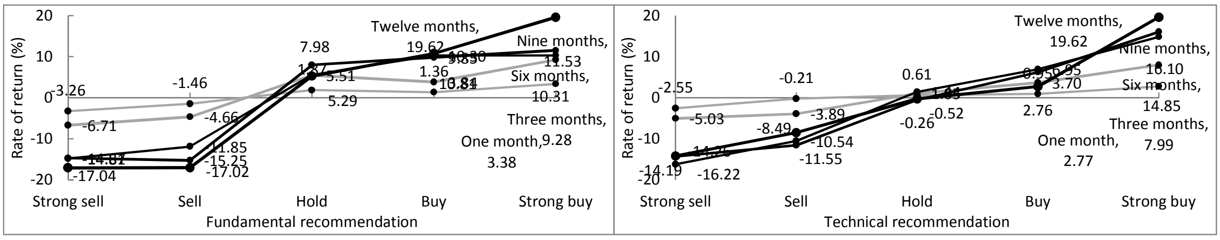
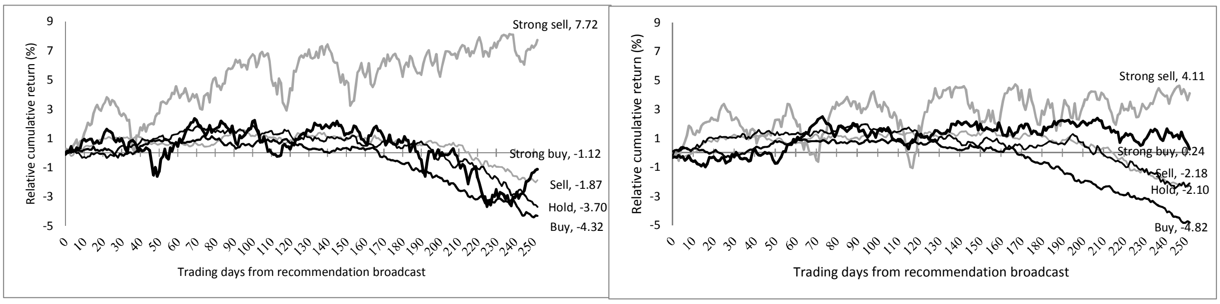


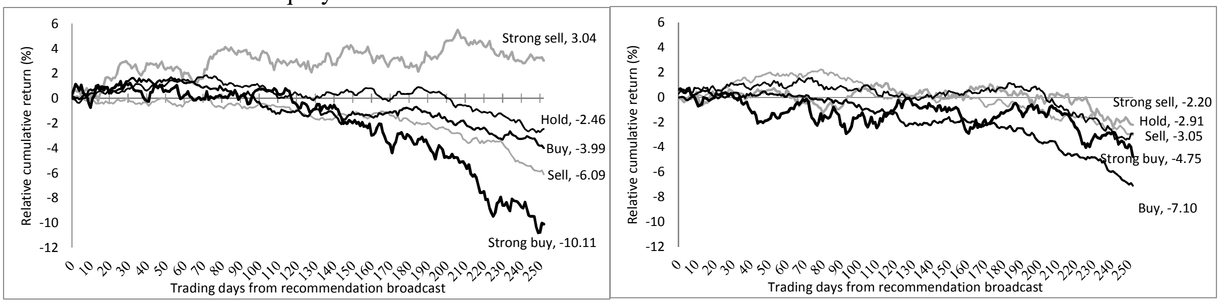
Figure 4. Average returns on various asset classes

The figures present the average returns on various assets over one, three, six, nine and twelve months after broadcasting fundamental recommendations (left-hand figures) and technical recommendations (right-hand figures). The underlying assets are the S&P 500 index, equity sectors and non-U.S. equity indexes, U.S. bonds, commodities and the U.S. dollar exchange rates.

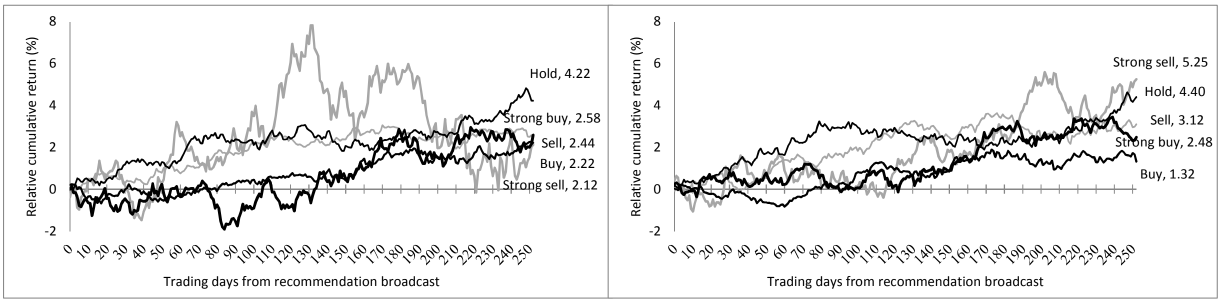
5a. S&P 500



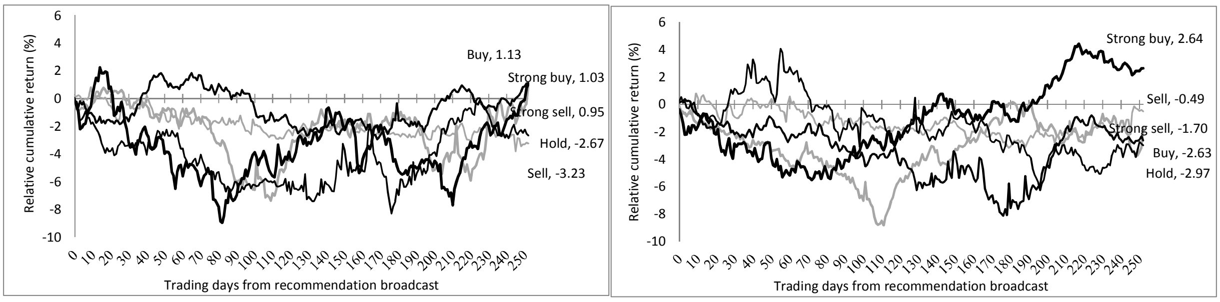
5b. Sectors and non-U.S. equity indexes



5c. U.S. bonds



5d. Commodities



5e. U.S. dollar

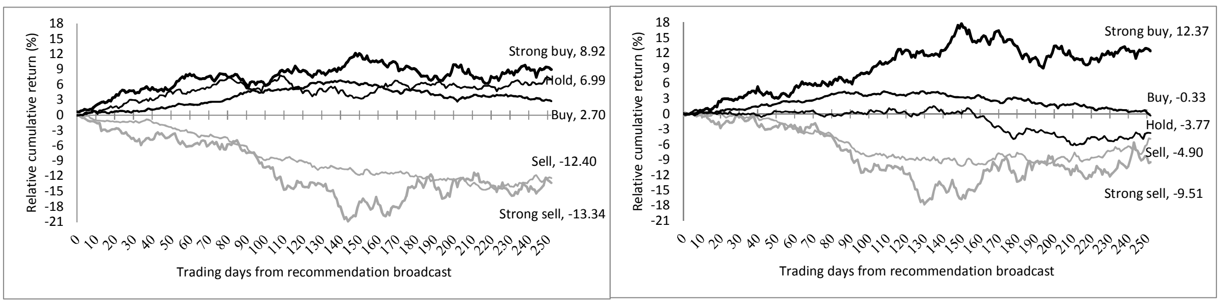


Figure 5. Relative cumulative returns on various asset classes

The figures present the cumulative returns less the mean returns on the S&P 500 index, equity sectors and non-U.S. equity indexes, U.S. bonds, commodities and the U.S. dollar for fundamental recommendations (left-hand-side figures) and technical recommendations (right-hand-side figures).

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.

<u>Strong sell</u>

"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 by Yahoo. Based on the strict "stay away" cite, we classified the fundamental recommendation as sell. Based on "looks very good," "very bullish indication," "plenty of more upside" and "continue to run," the technical recommendation was 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 by Yahoo, which is presented here for illustration purposes, as the full discussion usually includes more classification words and additional clarification.

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 the assets featured in “Talking Numbers”

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

Equity sectors and non-U.S. equity indexes
Sectors
S&P100, DOW INDASTRIAL, DOW UTILITIES, DOW TRANSPORTS, NASDAQ COMPOSITE, NASDAQ 100, RUSSEL2000, 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

Foreign Exchange rates
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