THE OHIO STATE UNIVERSITY
FISHER COLLEGE OF BUSINESS

Fisher College of Business
Working Paper Series

Charles A. Dice Center for Research in Financial Economics

Who benefits from Analyst "Top Picks"?

Justin Birru,
The Ohio State University

Sinan Gokkaya,
Ohio University

Xi Liu,
Miami University

René M. Stulz,
The Ohio State University, NBER and ECGI

Dice Center WP 2020-24
Fisher College of Business WP 2020-03-024
October 2020

Who benefits from Analyst "Top Picks"?

Justin Birru[a], Sinan Gokkaya[b], Xi Liu[c], and René M. Stulz[d]*

October 2020

Abstract

Following the Global Settlement, analysts extensively use a top pick designation to highlight their highest conviction best ideas. Such a designation enables analysts to provide greater granularity of information, but it can potentially be influenced by conflicts of interest. Examining a comprehensive sample of top picks, we find, even though top picks are more likely to be investment banking clients, they have greater investment value, attract greater media and investor attention, and lead to more trading. Top picks with poor ex post investment value are more likely to be influenced by strategic objectives and have adverse consequences for analysts. Institutions, but not retail investors, discern between top picks with good and poor ex post investment value.

[a] Fisher College of Business, The Ohio State University.
[b] Ohio University and a Visiting Scholar at Fisher College of Business.
[c] Farmer School of Business, Miami University.
[d] Fisher College of Business, The Ohio State University, NBER, and ECGI.

* We are grateful to Leandro Sanz for comments.
René Stulz consults and provides expert testimony on issues involving financial institutions that may employ analysts. None of his current or recent consulting concerns analysts.

1. Introduction

In the early 2000s, concerns about conflicts of interest of sell-side analysts led to new regulations and eventually to the Global Analyst Research Settlement. As discussed in Kadan, Madureira, Wang, and Zach (2009), one important byproduct of these regulations is the adoption of a new stock rating system by most leading investment banks. Before the Global Settlement, 85% of analyst recommendations are issued using a traditional five-tier rating system, but only less than 20% are afterwards.

Though a coarser three-tier rating system has the potential to reduce gains to analysts from engaging in strategic behavior, such a system also reduces the information available to investors. That is, sell-side analysts cannot fully discriminate among stocks whose performance they expect to be superior. To mitigate the costs of a coarser three-tier stock rating system, we would expect brokerage houses to attempt to increase the granularity of information available to financial market participants by devising new ways to draw attention to their best stocks. Consistently, we show that a new stock designation, "top picks," emerges following the Global Analyst Research Settlement and its use becomes widespread mostly among three-tier brokers. A top pick is typically the stock for which the analyst has the strongest conviction of superior performance compared to other buy recommendations. Notwithstanding the disproportionate amount of attention top picks receive from investors, media, and regulatory agencies, there exists no academic research on top picks we are aware of. A possible reason for this lack of research is that top picks are not identified on traditional databases academics rely upon (e.g., IBES). As a result, little is known about even basic details of top picks and whether analysts use top pick designations to give their best investment advice to investors, or are tempted to use these important designations to pursue strategic objectives that are not in the interest of investors.

Exploiting a novel and comprehensive sample of 3,563 top picks by 113 unique brokerage houses over 1999-2016, we find that top picks attract more retail, institutional and financial press attention and affect the trading of both institutional and retail investors more compared to buy recommendations. We investigate whether potential conflicts of interest affect the choice of top pick stocks and whether the market and investors can see through designations potentially tainted by conflicts of interest. Although investment banking clients are more likely to be selected as top picks, top pick designations, on average, have superior investment value for investors. Top picks with poor ex post investment performance are more likely to be investment banking clients. Though top pick designation announcements have a strong positive stock price reaction, the stock price reaction for top picks that have poor ex post performance is neither statistically nor economically significant, which suggests that the market does not credit poor top picks when they are announced. Top picks that have poor ex post performance are costly for analysts in that they worsen their career prospects and hurt their credibility with investors.

Top picks differ from stock recommendations in a number of ways.[1] First, a top pick is not a recommendation but an optional designation that represents an analyst's highest conviction "single best" idea within her coverage universe. In contrast, a buy recommendation typically means a stock is expected to outperform its industry peers. Hence, there can be at most only one top pick selection while there are multiple buy rated stocks outstanding by the same analyst at a given point in time. Second, unlike stock recommendations, "top pick" designations are assigned to a stock only for the upcoming one-year investment horizon (typically at the end or beginning of the year, with December, January, and February accounting for 66% of top pick announcements) and almost always expire on December 31st. Third, though analysts select their top pick stock from their buy recommendations, only 19% of top pick announcements coincide with a recommendation initiation, reiteration, or revision. In other words, the top pick designation represents a stand-alone analyst research output and we can directly assess its impact on financial markets. Fourth, top picks appear to be intentionally used as a marketing tool for brokerage houses. Indeed, a primary reason for the clustering of top picks in December – February is so that brokers can advertise stocks as top picks for the upcoming calendar year. In addition, brokers frequently organize best idea conferences to which they invite institutional clients and

[1] Throughout the paper, we use "buy rating" to also include "strong buy rating" when such a rating is employed by a brokerage firm. Occasionally, when the distinction is important, we refer to "strong buy" and "buy" ratings separately. Three-tier brokerages do not use the strong buy rating.

showcase their top pick selections, and product marketing teams periodically update investors about the performance of top pick selections through regular publications.

To further highlight the distinction between top picks and typical analyst recommendations, consider the following example. On December 17, 2012, an analyst from Barclays announced Penn National Gaming (henceforth, Penn) as her top pick for 2013 without changing or reiterating her recommendation, target price or EPS forecasts. The main investment thesis behind her top pick designation included Penn's conversion into a REIT structure to result in a higher trading multiple and Penn's robust dividend payout policy to attract both REIT and gaming operator investors. At the time of this top pick announcement, the analyst's coverage portfolio consisted of eight firms, including Boyd Gaming, Las Vegas Sands, Pinnacle Entertainment, Caesars Entertainment, MGM resorts, International Game Technology, Wynn Resorts and Penn, with five out of the eight coverage stocks holding a buy rating. According to Barclays, a top pick represents "the single best alpha-generating investment idea within each industry and is taken from among the Overweight-rated stocks within that industry". IBES does not record this top pick designation, or any others.

We start by documenting a number of facts regarding top picks. To begin with, top picks are increasingly common in the period following the regulatory changes of 2002. In 2000, before the reforms, only 5 firms are designated as top picks. In the year after the Global Analyst Research Settlement, there are 49 top picks. The number of top pick stocks continues to exhibit a steep upward trend in the years immediately following the Settlement. On average, from 2005 to 2016, there are 267 top picks every year. When we differentiate brokers based on their stock rating scales, we find that the vast majority of top picks are generated by brokers that switched from a five-tier to a coarser three-tier rating system following the new regulations.[2] Given that more than 50% of coverage stocks continue to be assigned a buy rating by sell-side analysts in the post-Global

[2]An important motivation behind the change in rating scales is Rule 2711 that requires brokers to disclose the percentage of stocks assigned buy, hold/neutral and sell recommendations in their coverage in each report (Kadan et al., 2009). Rule 2711 intends to help investors make better assessments of a broker's research and also curb analysts' strategic forecasting behavior.

Settlement period, we interpret these results as brokers attempting to increase information granularity and, potentially, strategic discretion, under a three-tier coarser rating system.

We find strong evidence that the top pick designation draws significant attention to a stock. We measure the attention of retail (institutional) investors by the Google Search Volume Index (Bloomberg search activity) and document that both retail and institutional investors devote more attention to announcements of top picks relative to that of buy recommendations in the same industry or in the same analyst's coverage universe. We next examine whether increased investor attention extends to the financial press and find more pronounced press coverage of top picks. In economic terms, 48% of top picks receive media coverage during the [0, +5] event window surrounding their announcements compared to only 25% (30%) for industry-year (analyst-year) matched buy recommendations. Furthermore, top picks are discussed in about three times as many financial news articles relative to buy recommendations.

Given the investor and media attention captured by top picks, we next seek to understand the potential motives underlying analysts' choice of top picks. The analyst could simply select a top pick with the intent of giving her best investment advice to investors. If this were the case, we expect top picks to be credible to investors if they believe that the analyst is skilled, so that they act on the recommendation and it has investment value. However, the exceptional stock distinction and greater attention-grabbing nature of top picks may potentially tempt an analyst to use the designation to pursue strategic objectives such as selecting a current or potential investment banking client as her top pick. This could potentially explain why we find that an investment bank affiliated stock, defined as the stock of a firm which used the investment bank for an IPO or a common stock issued over the last two years, is almost twice as likely to be designated as a top pick compared to unaffiliated stocks. If a stock is designated as a top pick for strategic reasons, the choice could have low investment value.

Diminishing potential concerns about strategic motives for top pick designations, we find strong evidence that these designations have investment value on average. For instance, a calendar-time portfolio comprised only of analysts' top picks earns roughly 1.33% characteristic-adjusted monthly returns (17.18% in annual terms) compared to only about 0.51% (6.29% in annual terms) for buy recommendations of the same analyst in a given year. In addition, the top picks' outperformance extends to buy recommendations issued in the same industry by other analysts. The evidence suggests that analysts exhibit skill in identifying their highest conviction best ideas and that strategic motives are unlikely to be important for an average top pick in that investors gain from following the investment advice. Conversely, consistent with Barber, Lehavy, McNichols, and Trueman (2001) and Altinkilic, Hansen, and Ye (2016), there is only weak evidence that buy recommendations have investment value for investors who take a position shortly after the announcement. Therefore, unlike their stock recommendations, sell-side analysts exhibit consistent long-term stock picking ability with their top picks, on average.

The investment value results show that analysts, on average, exhibit skill in designating top picks. However, not surprisingly, there is cross-sectional variation in the investment performance of top picks. In principle, the ex post poor performance of a top pick should be a surprise to investors if analysts are skilled and designate a stock as their top pick with high conviction. Hence, if poor performing top picks can be discerned when the designation is announced, it reflects either that the analyst making the designation lacks skill and is perceived as such by investors or that the analyst has skill on average but the designation is influenced by conflicts of interest. To identify top picks most (least) likely to reflect genuine best investment ideas, we separately focus on top picks in the top (bottom) quartile of ex post investment performance. We call top picks in the top (bottom) quartile good (bad) top picks. We find that bad top picks are more likely to be investment bank affiliated stocks. For these top picks, analysts do not expect significantly greater EPS and target price implied future stock returns. Therefore, the evidence is consistent with strategic objectives playing a role for a subset of top picks. However, if bad stock picks are designated to provide booster shots to investment banking clients, they do not appear to be helpful to these companies as the market is not fooled by such behavior. Specifically, we find that bad top picks are not associated with a significant positive stock price reaction. In sharp contrast, investment banking affiliation is not a significant predictor for good top picks but higher EPS forecasts and target price implied stock returns are. Moreover, good top picks are associated with significant positive stock price reactions.

We next turn our attention to trading behavior of financial market participants and examine whether institutional and retail investors value top picks and discern among bad and good top pick designations when they are announced. Examining institutional trading imbalances in the days around the top pick announcements with 286 million daily equity transactions obtained from *Ancerno Ltd.*, we find that institutional investors trade top picks at a greater intensity relative to stock recommendations, and seem to be able to discern whether a top pick is good or bad when it is announced. In economic terms, the average institutional buy-sell trading imbalance is 2.99% to 5.04% *higher* over the two-day event window surrounding the announcement of good top picks. In contrast, the average institutional trading imbalance is 3.5% to 4.7% *lower* over the same event window for bad top picks. Focusing on daily retail trading activity using Trade and Quote (TAQ), we document that retail trading imbalance is likewise greater for top picks relative to recommendations. However, unlike institutional investors, retail investors do not seem to distinguish among good and bad top picks.

Finally, we consider reputational and potential career implications of top picks for sell-side analysts. We uncover evidence suggesting that analysts pay a reputational cost for bad top picks. We find that the stock-price reaction to recommendation upgrades/downgrades by an analyst is lower in the year after the same analyst makes a bad top pick selection, consistent with the marketplace disciplining bad top pick selections. We also find that analysts that make bad top pick recommendations are more likely to be demoted to lower ranked brokerage houses. Further, analysts that make good top picks are more likely to be subsequently selected to the all-American team.

Our paper makes contributions to multiple segments of the literature focused on sell-side analysts and their outputs. First, we contribute to the vast body of analyst literature attempting to identify the most influential stock recommendations and sell-side analysts' stock picking skill based on a set of individual analyst or brokerage house characteristics (see, for instance, Stickel, 1992, Clement, 1999, Asquith, Mikhail, and Au, 2005, and Bae, Stulz, and Tan, 2008), stock-level abnormal returns, or the state of the economy (Loh and Stulz, 2018). In this paper, we take a novel approach and identify the most influential recommendations from the *analysts'* point of view. Our results suggest that top pick designations have to be considered when evaluating the role of analysts and their performance.

Second, we add to the literature that seeks to understand the implications of the regulatory environment on sell-side research and potential conflicts of interest emanating from investment banking business. Buy (hold/sell) stock recommendations have become less (more) common following the Global Analyst Research Settlement (e.g., Barber, Lehavy, McNichols, and Trueman, 2006, and Clarke, Khorana, Patel, and Rau, 2011) and there is evidence of a reduction in investment banking related strategic behavior (Corwin, Larocque and Stegemoller, 2017). Kadan et al., (2009) also show that most investment banks transition from a traditional five-tier rating system to a coarser three-tier rating system in the post-Settlement period. We add to this literature by documenting that regulations have been followed by a new "top pick" designation adopted by brokers transitioning to a coarser three-tier rating system. While this designation is valuable to investors on average, we cannot exclude that strategic concerns at times play a role in top pick designations in that top picks with poor investment value are more likely to be firms that are investment banking clients.

Third, we contribute to the literature that examines whether institutional investors can sort through Wall-Street research and discern among good and bad stock recommendations. For example, Malmendier and Shanthikumar (2007), Mikhail, Walther and Willis (2007) and others show institutions trade only good stock recommendations. In contrast, Busse, Green, and Jegadeesh (2012) fail to uncover empirical evidence that institutions can differentiate among analyst recommendations. Exploiting the unique and important laboratory provided by analyst' top picks, we revisit this important research question and document that institutions can distinguish between good and bad top picks when they are announced and trade more (less) actively when they believe that a top pick represents a good (bad) stock selection.

Fourth, we add to the literature pioneered by Hong, Kubik and Solomon (2000) and Hong and Kubik (2003) that examines the role of career concerns for analysts, how analysts are rewarded by investors and employers for their performance, and how their actions affect the credibility of recommendations and formation of their reputations. We use a novel setting that purportedly represents analyst's highest conviction best ideas. We find that analysts benefit from making good top pick choices, but they get punished in the labor market and suffer reputational consequences for making bad ones.

The paper proceeds as follows. Section 2 provides institutional background on top picks and describes our sample. Section 3 assesses the attention paid to top picks. Section 4 examines the characteristics of top pick selections. Section 5 measures the investment value of top picks. Section 6 sheds light on top pick motives and whether financial market participants can discern among good and bad top picks. Section 7 explores the career and reputational consequences of good and bad top pick designations for analysts. Section 8 concludes.

2. Institutional Background, Sample, and Summary Statistics

In 2002, the NYSE adopted Rule 472, NASD adopted Rule 2711, and ten of the largest US investment firms entered an enforcement agreement with the SEC, the NASD, and the NYSE to address investment banking related potential conflicts of interest concerning stock recommendations by sell-side analysts. Regulators believed that these conflicts of interest led analysts to make too optimistic stock recommendation decisions for strategic reasons, such as helping their firm's investment banking arm. Before these regulatory changes and enforcement actions, it was typical for analysts to use a five-tier system for their recommendations, where they had both buy and strong buy recommendations. After 2002, all sanctioned investment firms and most other brokerage houses transition to a three-tier system and investors lose the benefit of a more granular rating system (e.g., Kadan et al., 2009). Absent strategic forecasting behavior emanating from conflicts of interest, investors benefit more from a more granular stock rating system, at least up to a point. With a finer gradation, analysts can distinguish among stocks that they expect to perform well and stocks whose performance they expect to be even better. However, potential conflicts of interest may lead to situations where analysts issue strong buys for strategic reasons such as increasing the likelihood of their firms being hired as underwriters or providing booster shots to investment banking clients (see Mehran and Stulz, 2007, for a review of this literature). A three-tier rating system reduces the benefit to analysts from acting strategically.

After the Global Settlement, brokerage houses extensively use a top pick designation to distinguish their top stocks. A top pick is not a stock rating, but an optional designation and is distinct from buy recommendations along various dimensions. First, a top pick represents an analyst's "highest conviction best idea" among her coverage portfolio of stocks while a buy recommendation means, on average, a stock is expected to outperform its industry peers. In other words, although an analyst may have multiple buy recommended stocks, there can be at most only *one* top pick in an analyst's coverage portfolio in a given year. Further, while the vast majority of analysts have at least one buy recommended stock in their coverage universe, they issue top pick designations much less frequently. Second, a stock can typically have a top pick designation only for the upcoming one-year investment horizon and it typically expires on December 31st of the year a stock is given a top pick status for (unless reiterated or removed before its expiration). In contrast, buy recommendations extend over an unspecified investment horizon, and don't expire at the end of a calendar year with a sizable fraction being neglected (i.e., not dropped, revised or reiterated) by the analyst (e.g., Boulland, Ornthanalai, and Womack, 2017). Third, analysts generally announce top pick status for a coverage stock between November and February while buy recommendation announcements do not exhibit such time clustering across months. Our conversations with current sell-side equity analysts also indicate that analysts take the top pick selection process very seriously — they say that they commit a significant amount of time identifying top picks, the investment thesis, and the conviction behind the choice underlying their top picks. Further, analysts publicize top picks within their brokerage houses, present them to and interact with institutional investors during broker-sponsored "best idea" conferences, and draw attention to them with media appearances. Lastly, product marketing and equity research teams at brokerage houses periodically update investors about top pick stocks' performance with monthly/quarterly publications.

Traditional databases academics rely on (i.e., IBES) do not carry information about the top pick status of stocks covered by analysts. Therefore, following conversations with sell-side analysts currently employed at bulge bracket investment banks, we manually construct a comprehensive sample of top picks from Thomson *Reuters Investext* and *Thomson Reuters Eikon* by searching each full-text analyst report for discussions on the variants of "top pick & best idea."[3] Overall, we have a comprehensive sample of 3,563 top picks identified by 113 unique brokers over 1999-2016.

Table 1 provides yearly descriptive statistics for our sample. Corroborating Kadan et al., (2009), we find that there is a widespread transition to three-tier scale rating systems among brokerage houses after 2002. In 2001, 31.60% of brokers use a three-tier system and 14.60% of stocks are covered by three-tier brokers. These figures sharply increase to greater than 60% in 2003 and further exceed 70% from 2004 on. All ten original investment banks that signed the Global Settlement in 2002 (joined by Deutsche Bank and Thomas Weisel in 2004) transitioned to a coarser three-tier rating system shortly after.

Following the transition from a five-tier to a three-tier rating system, the potential gains to analysts from engaging in strategic behavior are sharply lower because receiving a "buy" recommendation is not in any way receiving an exceptional distinction. However, investors lose the benefit from finer gradation in ratings due to the removal of strong buy ratings. While the distribution of buy rated stocks becomes more balanced after 2002, more than 50% of coverage stocks continue to be assigned a "buy" recommendation by three-tier brokers. If these gradations were valuable to investors or enabled analysts to act strategically, we expect them to resurface. Consistently, Panel B shows that the Global Analyst Research Settlement is followed by the emergence of, and the steady increase in the new top pick designation. The first column shows that there are only 17 top pick firms in total between the years 1999 and 2001. The number of top pick stocks, however, exhibits a steep upward trend in the years following the regulations enacted in 2002. In 2003, there are 49 top pick firms and this figure increases to 128 in 2004, and 200 in 2005. In the last six years of our sample period, there are at least 300 top picks identified by analysts each year.

[3] To finalize our list of bigram word combinations, we download and read 100 randomly identified analyst reports and summarize the way analysts discuss their top pick stocks. Our complete keyword list is (Top or Best) AND (idea or pick). Next, we download and manually verify each observation by reading the title, table of contents and full body of the report to ascertain a firm is explicitly assigned a top pick status. For the sake of being conservative, we purge any observation for which there is ambiguity on the top pick designation of a coverage firm. We collect information on the name of coverage firm designated as top pick, sell-side analyst and brokerage house authoring the report, date of the report, investment horizon (i.e., calendar year a stock is designated as top pick for) and expiration date of top pick status.

We distinguish brokerage houses by rating scales and find that the vast majority of top picks are generated by three-tier brokers following the market regulations aimed at curbing investment banking-related conflicts of interest. This is potentially consistent with three-tier brokers attempting to increase rating granularity or strategic discretion. Since each analyst can at most have one top pick (if any) in a given year, it is not surprising that top pick firms represent only 0.16% of buy rated stocks by three-tier brokers in 2003, reaching a peak of 1.86% in 2008. In contrast to a buy recommendation, a top pick designation is an exceptional distinction for a coverage stock.

Panel C examines how frequently top pick announcements overlap with announcements of stock recommendations in IBES. Only 7% of top picks are announced jointly with a recommendation change or a reiteration and 14.7% overlap with recommendation initiations. This lack of overlap suggests that we can directly isolate the association between top picks and financial market attention, investment value of analyst research, market reaction, and institutional/retail investors' trading behavior. In the remainder of our paper, we focus on top pick designations that do not overlap with stock recommendations.

In Panel D, we report the distribution of top pick announcements across months and find that more than two-thirds of top picks are announced in December, January, or February, and nearly 80% of top picks are issued between November and March. In untabulated analyses, we document that 81.21% of stocks keep their top pick designation only for one investment year or less while the remaining top picks (roughly 18%) keep their designations for another year or more.

3. Top Picks and Financial Market Attention

The clustering of top pick announcements around the turn of the year enables brokerages to implement top pick marketing strategies where they can publicize these top picks collectively. Brokerages devote considerable attention to publicizing their top pick selections. They do so through broker hosted investor conferences devoted to top picks as well as through media appearances. In this section, we investigate whether top picks capture the attention of investors and whether the attention to top picks by retail investors differs from that of institutional investors. We then show the extent to which the financial press covers top picks relative to buy recommendations.

3.1. Retail and Institutional Investor Attention.

To measure the attention of retail investors to top picks, we follow related work and focus on the average Google Search Volume Index (GSVI) (see, e.g., Da, Engelberg, and Gao, 2011, and Focke, Ruenzi and Ungeheuer, 2020) over the (0,+5) event window surrounding the announcement of analyst research outputs. We input each stock ticker in Google Trends and download daily GSVI from 2004 to 2016. As indicated by Da, Engelberg, and Gao (2011), this methodology follows the logic that people searching financial information in Google with a stock ticker are more likely to represent retail investors as opposed to institutional investors since the latter group of investors typically use Bloomberg terminals for financial research purposes. In an attempt to make the data collection and screening process more manageable, we restrict our analysis to S&P 500 firms. We further measure the surge in retail investor attention with normalized GSVI. To do so, we calculate an abnormal retail attention (AGSVI) measure that subtracts the median value of GSVI over the eight weeks preceding the announcement of a corresponding analyst research output from the raw level of GSVI.

To measure institutional investors' attention, we measure their search activity on Bloomberg terminals. This approach is originally introduced by Ben-Rephael, Da, and Israelsen (2017) and is employed by a growing strand of academic literature (e.g., Focke, Ruenzi and Ungeheuer, 2020, and Gibbon, Illiev and Kalodimos, 2020). Bloomberg records the number of times users actively search for and read news articles on a specific stock and assigns a score of 1, 2, 3 or 4 if the average is between the 80th and 90th percentile, the 90th and 94th percentile, the 94th and 96th percentile, or exceeding the 96th percentile of the rolling average over the previous 30 days, respectively. Bloomberg also assigns a score of 0 if the average is less than the 80th percentile of the past 30 days' hourly counts. Consistent with Ben-Rephael, Da, and Israelsen (2017), we transform Bloomberg's score to continuous values with Bloomberg search scores taking the value of -0.350, 1.045, 1.409, 1.647 and

2.154, respectively. Similar to our retail attention measures, we restrict the institutional attention analysis to S&P 500 firms and calculate the average Bloomberg scores over [0,+5] relative to the announcement of analyst research.

As a starting point for our analysis, we compare the univariate differences of retail and institutional investor attention across top picks and buy recommendations issued for stocks within the same industry in the same year. Industries are classified using 4-digit Global Industry Classification Standard (GICS) codes. Boni and Womack (2006) indicate that GICS industry codes match well with sell-side industry research practice. Comparison of top picks to buy recommendations issued in the same industry in the same year further ensures that any difference in the attention to top picks and buy recommendations is unlikely to be driven by economic conditions specific to a given industry in a given year.

Panel A of Table 2 presents the univariate analyses. We find that retail and institutional investors appear to devote more attention to the announcement of top pick designations relative to that of buy recommendations. A plausible concern with these univariate comparisons is that market participants may focus on a subset of analysts and devote more attention to their research irrespective of its content. If top picks are more likely to be generated by attention-grabbing analysts, then our univariate inferences may potentially be biased. Therefore, Panel B of Table 2 compares investor attention devoted to analysts' top picks to the *same* analyst's buy recommendations in the *same* year. Our inferences remain similar.

In Panel C of Table 2, we employ panel regressions that regress GSVI, AGSVI, and Bloomberg search measures on a battery of analyst and firm specific covariates. We include a broad set of firm, analyst, and forecast-level characteristics that may also be correlated with retail and institutional attention. Our independent covariates include proxies for analyst forecasting ability including firm-specific and general forecasting experience, portfolio size and complexity, All-star status (*Fexp, Gexp, Portsize, Port Gics, All-Star*), forecast specific variables, including analyst effort (*Drop Coverage*), optimistic EPS forecasts relative to consensus estimates (*Relative EPS Optimism*), investment banking affiliation based on initial public/seasoned equity offerings (IPO or SEO) by coverage firm *i* in the past 24 months (*Investment Bank Affiliation*), and a binary indicator variable which equals one if the recommendation is rated a strong buy (*Strong Buy*). Moreover, we isolate brokerage house characteristics with the broker size and industry specialization (*Top 10, Broker ind specialization*). In terms of firm characteristics, we control for firm size (*Size*), book-to-market (*BM*), stock turnover (*Turnover*), institutional ownership (*Institutional holding*), number of analysts following the stock (*SSA coverage*), idiosyncratic volatility (*Idiosyncratic volatility*), earnings forecast dispersion (*Dispersion*), and past 12-month abnormal stock returns (*Past 12 m return*). Appendix A provides detailed information on the construction of variables. Finally, we include industry-year (or analyst-year) paired fixed effects and report heteroskedastic consistent standard errors clustered at the analyst and firm level. Formally, our model is as follows (we omit the time and stock subscripts):

$$GSVI/AGVI/Bloomberg\ Search = \beta_1\, Top\ Pick + \beta_2\, Strong\ Buy + \beta_3\, Size + \beta_4\, BM + \beta_5\, Institutional\ Holding + \beta_6\, Turnover + \beta_7\, SSA\ Coverage + \beta_8\, Idiosyncratic\ Volatility + \beta_9\, Dispersion + \beta_{10}\, Past\ 12\text{-}m\ return + \beta_{11}\, Fexp + \beta_{12}\, Gexp + \beta_{13}\, Portfolio\ Size + \beta_{14}\, Portfolio\ GICS + \beta_{15}\, Relative\ EPS\ Optimism + \beta_{16}\, All\text{-}star + \beta_{17}\, Drop\ Coverage + \beta_{18}\, Top\ 10\ Broker + \beta_{19}\, Investment\ Bank\ Affiliation + \beta_{20}\, Broker\ Industry\ Specialization + Industry{*}Year\ Fixed\ Effects/Analyst{*}Year\ Fixed\ Effects + \varepsilon \qquad (1)$$

Models 1 and 2 of Panel C in Table 2 show that a top pick designation draws significantly higher raw and abnormal retail investor attention relative to buy recommendations in the same industry and year over [0,+5] days surrounding the announcement of analyst research. In Model 3, we repeat analogous analyses for institutional investors and find that analysts' top picks also attract higher abnormal attention from institutional investors. In the last three columns, we benchmark top picks against buy recommendations generated by the same analyst at the same point in time and continue to illustrate the relatively higher attention-grabbing nature of top picks. It is noteworthy that these regressions show that investors pay less attention to recommendations of analysts for coverage firms with which their investment bank arm has an affiliation. This suggests that both retail and institutional investors distinguish between stocks where there is a potential conflict of interest and others. Such a result suggests that strategic recommendations may face investor skepticism.

3.2. Financial Press Coverage

The results thus far show that financial market participants devote more attention to analysts' top picks than to their buy recommendations. We next examine whether increased attention extends to the financial press coverage.

To test this conjecture, we construct our sample of financial media coverage data from *RavenPack's Dow Jones Edition* that includes news articles from *Dow Jones Newswire* and *The Wall Street Journal*.[4] Our data screening process includes matching each top pick and recommendation announcement to a financial news piece and then manually checking each article's headline (using the information on the brokerage house's name and direction of research) to ascertain we have the correct news article. We focus on financial media articles published on days [0, +5] relative to the announcement of analyst research.[5]

Table 3 presents results for media attention to top picks. The first column of Panel A shows that roughly 48% of top picks receive media coverage during the [0, +5] event window surrounding top pick announcements. In contrast, the next column documents that approximately only one-fourth of buy recommendations sharing the same industry and year are covered by the financial press, a figure consistent with past studies (e.g., Ahn, Drake, Kyung and Stice, 2019). The difference is not only statistically significant but also economically meaningful (last column). More striking is the difference in the intensity of media coverage. The bottom row of Panel A shows that top picks are discussed in about three times as many news articles as buy recommendations (1.95 vs 0.66).

[4] Dow Jones News and Ravenpack have been extensively employed in numerous finance studies such as, Barber and Odean (2007); Tetlock (2010); Ben-Rephael, Da and Israelsen (2017)

[5] Results are similar when we consider financial press coverage over shorter event windows (i.e., [0, +2]; [0, +3]; [0, +4]) or longer event windows (i.e., [0, +10]) surrounding the announcement of top picks. Results are available from authors upon request.

An important concern with our univariate analysis in Panel A is that the financial press tends to focus on a subset of "celebrity" analysts and devotes more news articles to such analysts' research in their news pieces (e.g., Bonner, Hugo and Walther, 2007). If top picks are issued by such celebrity analysts, then our univariate inferences may potentially be misleading. To alleviate this concern, Panel B compares financial press coverage devoted to top picks with that of buy recommendations by the same top pick issuing analyst at the same point in time. Our evidence supports a positive association between a stock's top pick status and coverage by the financial press.

In Panel C, we employ multivariate OLS regressions to test the hypothesis that top picks attract more media attention than buy recommendations. Our dependent variable is equal to the number of news articles devoted to a top pick designation or buy recommendation by analyst *i* at time *t*. Once again, since these characteristics may also be correlated with the intensity of financial press coverage, we include controls for the battery of firm- and analyst-level characteristics introduced in Section 3.1. Finally, we include industry-year or analyst-year paired fixed effects and report heteroskedastic consistent standard errors clustered at the analyst and firm level.

In Panel C of Table 3, the coefficient estimate on *Top Pick* is positive and statistically significant in Model 1 (*t*-statistic of 25.88). In economic terms, the announcement of analysts' top picks are associated with 1.14 more news articles by the financial press relative to that of buy recommendations. To put this result in perspective, All-star ranked analysts generate 0.13 more news pieces by the financial media. Other control variables also have expected signs. For instance, the financial media devotes more attention to research by sell-side analysts possessing longer firm-specific and general forecasting experience. In Model 2, we re-estimate our econometric specifications by focusing only on top pick issuing analysts with the inclusion of analyst-year paired fixed effects. Essentially, this setting compares press coverage on each analyst's top pick relative to buy recommendations in the same analyst's coverage portfolio within the same point in time. This methodology has the added benefit of isolating the time-varying analyst specific characteristics that may be also potentially correlated with financial media attention (including her celebrity status). The evidence again indicates top picks receive considerably higher media attention when compared to buy recommendations issued by the same analyst at the same year. While investors pay less attention to stock recommendations for affiliated stocks, there is no significant evidence that the media pays less attention to analyst research on such stocks.

Taken as a whole, the empirical evidence presented in Section 3 lends support to the notion that the top pick designation generates more pronounced attention by retail and institutional investors as well as the financial press. While these results may be a manifestation of the top pick designation being assigned non-strategically to represent analysts' genuine best ideas, and therefore perceived to convey more information than a buy recommendation, it is also plausible that analysts strategically assign top pick status to seek increased exposure and visibility for investment banking clients. Hence, in Section 4, we turn to examining the characteristics of top picks relative to buy recommendations.

4. Characteristics of Top Picks

To understand the potential underlying motives driving analysts' choice of top pick firms, we next examine how firm and forecasting characteristics differ between top picks and stocks with buy ratings. We estimate logistic regression models where the dependent variable is a binary indicator that equals one if stock *j* is assigned a top pick designation by analyst *i* for year *t*, and zero if a stock operates in the same industry, is rated buy in year *t*, and does not carry a top pick status. In addition to the host of firm specific characteristics introduced in Section 3.1, we further consider the forecasted stock return implied by analyst *i*'s target price (%*Target price implied return*) on stock *j*. Our logistic regressions include industry-year (or analyst-year) paired fixed effects and continues to report standard errors that are heteroskedastic consistent and double clustered at the analyst and firm level. Formally, our model is as follows (we omit the time and stock subscripts):

$$(Top\ Pick=1) = \beta_1\ Size + \beta_2\ BM + \beta_3\ Institutional\ Holding + \beta_4\ Turnover + \beta_5\ SSA\ Coverage + \beta_6\ Idiosyncratic\ Volatility + \beta_7\ Dispersion + \beta_8\ Past\ 12\text{-}m\ return + \beta_9\ Investment\ Banking\ Affiliation + \beta_{10}\ Relative\ EPS\ Optimism + \beta_{11}\ Target\ Price\ Implied\ Return\ (\%) + \beta_{12}\ Target\ Price\ Implied\ Return\ Rank\ \#1/\#2/\#3/\#4/\#5 + Industry*Year\ Fixed\ Effects/Analyst*Year\ Fixed\ Effects + \varepsilon \qquad (2)$$

Model 1 of Table 4 compares top picks with buy recommendations and illustrates that top pick stocks tend to be relatively larger and are also more likely to be growth and momentum stocks as measured by the book-to-market ratio and the past 12-month returns. We further discover that top pick stocks are more visible to the investment community as evidenced by higher institutional ownership and more intense sell-side analyst coverage. Additional results indicate that the likelihood of a stock being identified as top pick is negatively associated with the level of uncertainty and diversity of opinion surrounding a stock as evidenced by lower idiosyncratic volatility and earnings forecast dispersion.

Focusing on analyst forecasts, the positive coefficient estimates on relative EPS optimism and target price implied returns are consistent with analysts expecting higher EPS and stock return performance from top picks compared to buy recommendations. For example, a one standard deviation increase in relative EPS optimism (%target price implied returns) increases the odds of a stock being designated top pick by 12.74% (21.63%) relative to buy recommended stocks without a top pick designation. Interestingly, we also uncover empirical evidence pointing to potential investment banking related "strategic bias" underlying the selection of top pick stocks — analysts are more likely to select investment banking clients as their top picks and the economic significance of investment banking affiliation on top pick selection is substantial. Specifically, investment bank affiliated stocks are associated with 97.56% higher likelihood of being designated as top picks relative to unaffiliated stocks. In unreported analyses, we consider alternative definitions of investment banking affiliation and continue to find similar results.[6]

In Models 2 and 3, we focus only on analysts issuing at least one top pick and re-estimate logistic regressions with the inclusion of analyst-year paired fixed effects. That is, we compare the attributes of top pick

[6] Untabulated analyses consider alternative definitions of investment banking affiliation by focusing on IPOs or SEOs underwritten by analyst's investment banking units six or twelve months preceding the announcement of analyst research. The results are similar and available upon request.

stocks to buy recommendations generated by the same analyst in the same year. Again, our main inferences remain unchanged — top picks look different from buy recommendations within an analyst's portfolio.

A top pick designation would be uninformative if all that an analyst does is select the stock with the highest expected price appreciation as her top pick. To examine this possibility, Model 3 includes a binary indicator variable for the ranking of the stock's target price implied percentage return (i.e., highest rank of 1, 2, 3, 4, and 5) relative to other buy-rated stocks in the same analyst's coverage universe in the same year. While stocks with the highest target price implied returns are more likely to be selected as top picks relative to other buy rated stocks in an analyst's portfolios, the coefficient estimate for stocks with the highest target price implied returns (i.e., rank 1) is not significantly larger than for stocks ranked 2, 3, and 4 This is consistent with the interpretation that analysts do not simply follow a mechanical rule of selecting stocks with the highest target price implied stock returns as their top picks, but instead, take into account other considerations when identifying their highest conviction best ideas. These other considerations may be influenced by potential conflicts of interest, and if they are, we would expect top picks to have poor investment value. We investigate investment value next.

5. Investment Value of Top Picks

If stocks are given a top pick status for strategic reasons such as providing a booster shot to investment banking clients, or helping the investment banking arm win future mandates, or capturing financial market attention and publicity for a favored firm, then we would not expect stocks with top pick status to outperform buy recommended stocks. On the other hand, if analysts confer top pick status on stocks for which they have the highest conviction with regards to superior future performance and analysts possess stock picking skills in identifying top picks, then we expect top pick status to be informative for future returns.

As a first step towards providing answers to this question, we employ an investor-oriented calendar-time portfolio approach. We follow Barber, Lehavy, McNichols and Trueman (2006) and construct a portfolio comprised of top picks and a portfolio comprised of industry-year matched buy/strong buy recommendations, but without a top pick designation. For the investment portfolio of top picks, we start by identifying the announcement date of a top pick designation and then skip a trading day before inclusion into the portfolio to ensure the information on top picks is publicly available to all market participants. For instance, if a stock is announced as a 2016 top pick on January 3rd of 2016, the stock enters the top pick portfolio on January 4th and exits the calendar-time portfolio on December 31st of 2016 (unless reiterated for the next year or the analyst removes the top pick designation before December 31st of 2016). We rebalance top pick portfolios on a daily basis when a new top pick is announced or current top pick designation expires, is reiterated, or removed before its expiration. For the portfolios of buy recommendations, we follow an analogous methodology with the exception of expiration dates. As indicated earlier, stock recommendations do not expire at the end of a calendar year nor do they have an investment horizon. To understand the investment value of top picks relative to buy recommendations, we calculate portfolio excess stock returns with a multitude of characteristic and risk adjustments, including Daniel, Grinblatt, Titman and Wermers (1997)'s (henceforth DGTW) characteristic-adjusted returns, risk-adjusted portfolio returns from the Fama and French (1993) three-factor model (*3-Factor alpha*), the Carhart (1997) momentum factor model (*4-Factor alpha)*, the Pastor and Stambaugh (2003) liquidity factor model (*5-Factor alpha)* as well as Fama-French's short-term and long-term reversal factor models (*6*- and *7-Factor alpha).*

Panel A of Table 5 presents the results. Comparing excess stock returns accrued to top picks with those to buy stock recommendations generated by the *same* analyst during the *same* year, we find that a calendar-time investment portfolio comprised only of analysts' top picks generates DGTW-adjusted monthly returns of 1.33% (17.18% in annual terms). Buy recommendations, on the other hand, yield only about 0.51% DGTW-adjusted returns on a monthly basis (6.29% in annual terms). The difference is not only statistically significant at conventional levels (*t*-statistic for the difference is 3.25), but also economically important. These results are likewise robust to measuring excess stock returns using the factor models listed in the previous paragraph. Therefore, it appears that analysts' top picks carry significantly greater investment value for financial market participants than buy stock recommendations issued by the same analysts.

In Panel B, we investigate whether top picks' outperformance extends to stock recommendations outstanding in the same industry during the same calendar year (excluding recommendations of top pick analyst). As discussed earlier, analysts characterize top picks as representing their highest conviction "best idea" among the stocks they cover. We expect top picks to outperform same industry-year buy/strong buy recommendations issued by *other* analysts only if top picks also represent the best ideas in a given industry. If so, one should consider a stock's top pick designation when analyzing the information content of *all* stock recommendations, not just the recommendations generated by the top pick analysts. Panel B presents the results. Consistent with top picks representing the best stock investment ideas in an industry, the last column shows that DGTW-adjusted monthly returns accrued to top pick stocks are 90 basis points higher relative to that of positive recommendations in the same industry and year (*t*-statistic for the difference is 4.17). The remaining rows show that the magnitude of differences between top picks and same industry-year buy/strong buy recommendations is even larger, ranging between 110 and 120 basis points when using risk adjustments of the Fama and French (1993) three-factor model (*3-Factor alpha)* and when we add to that model, in succession, the Carhart (1997) momentum factor (*4-Factor alpha)*, the Pastor and Stambaugh (2003) liquidity factor (*5-Factor alpha)*, the Fama-French short-term reversal factor (*6-Factor alpha)*, and the long-term reversal factor (*7-Factor alpha).* In untabulated analyses, we further stratify buy stock recommendations into strong buys and buys and document results with comparable economic magnitudes to those in Panel B.

A logical concern with the analyses in Panel B of Table 5 is that analysts identifying top picks may possess superior stock picking skills relative to analysts not issuing top picks so that our results may be biased by the differences across analysts' forecasting ability. To alleviate this concern, Appendix Table A1 compares buy recommendations of analysts who use the top pick designation with industry-year matched buy recommendations of analysts who do not use the designation. The return differences range between 8 and 24 basis points per month depending on characteristic and risk adjustments – however, none of the differences are statistically significant at conventional levels.

Another concern with analyses in Panels A and B is that elevated financial market attention accompanying the announcement of top pick stocks may prompt investors to buy such stocks at a greater propensity relative to recommendations (see Barber and Odean, 2008, for evidence that elevated financial market attention leads to more trading). If so, temporary short-term buying pressure may potentially bias our estimates (especially in the short-term). To address this concern, Appendix Table A2 skips five trading days after the announcement of analyst research and buys the stock at day t+6 relative to the announcement date as opposed to day t+1. Excluding the days immediately after the announcement of a top pick does not change our inferences about the investment value of top pick designations compared to buy recommendations. For instance, characteristic-adjusted (*7-factor alpha*) monthly returns to top picks are roughly 106 (104) basis points after excluding [0, +5] event window surrounding the announcement of analyst research. Top picks also continue to outperform buy/strong buy recommendations issued in the same industry and year by between 80 and 114 basis points, depending on risk-adjustment. Though top picks have significant investment performance irrespective of how we measure excess stock returns, buy recommendations have significant investment performance only with the DGTW approach. This evidence suggests that if an investor starts investing in a top pick stock or a buy recommended stock five trading days after the announcement, there is strong evidence of investment performance for the top pick designation but almost no evidence of investment performance for buy recommendations, highlighting the importance of investors acting quickly to generate returns on analyst buy recommendations as suggested by Barber, Lehavy, McNichols and Trueman (2001) and Altinkilic, Hansen and Ye (2016).

In Table 6, we consider the panel regression methodology adopted by past related work (e.g., Cohen, Frazzini, and Malloy, 2010) to ensure our results are not driven by uncontrolled firm, analyst, and broker specific characteristics. While the dependent variable is the daily abnormal DGTW-adjusted return, we convert coefficient estimates into monthly returns for ease of interpretation. Analogous to the calendar-time portfolio methodology, we exclude the trading day of the top pick or buy recommendation announcement. Our key independent variable of interest is "Top Pick", which is an indicator variable equal to one if a stock j is given top pick status by analyst i for year t. Regressions include combinations of year-month, industry-year, and analyst-year fixed effects. The full regression specification (omitting time and firm subscript) is:

$$\text{DGTW adjusted return} = \beta_1 \text{Top Pick} + \beta_2 \text{Strong Buy} + \beta_3 \text{Size} + \beta_4 \text{BM} + \beta_5 \text{Institutional Holding} + \beta_6 \text{Turnover} + \beta_7 \text{SSA Coverage} + \beta_8 \text{Idiosyncratic Volatility} + \beta_9 \text{Dispersion} + \beta_{10} \text{Past 12- m return} + \beta_{11} \text{Fexp} + \beta_{12} \text{Gexp} + \beta_{13} \text{Portfolio Size} + \beta_{14} \text{Portfolio GICS} + \beta_{15} \text{Relative EPS Optimism} + \beta_{16} \text{All-star} + \beta_{17} \text{Drop Coverage} + \beta_{18} \text{Top 10 Broker} + \beta_{19} \text{Investment Banking Affiliation} + \beta_{20} \text{Broker Ind Specialization} + \text{Year-Month Fixed Effects} + \text{Analyst*Year Fixed Effects/Industry*Year Fixed Effects} + \varepsilon \qquad (3)$$

Model 1 of Table 6 reports regression results with analyst-year fixed effects. The coefficient estimate on *Top pick* is positive and significant, suggesting that top picks outperform buy recommendations issued by the same analyst during the same year. In Model 2, we include industry-year paired fixed effects to investigate whether top pick stocks' outperformance extends to industry-year matched buy/strong buy recommendations generated by *other* analysts. The positive coefficient estimate on *Top Pick* corroborates the earlier results. In economic terms, top pick stocks yield a higher monthly abnormal DGTW-adjusted return of 0.84 percentage points compared to industry-year matched stock recommendations of other analysts. Models 3 and 4 exclude stock returns between day t+1 and t+5 to mitigate the potential influence of heightened market attention on our coefficient estimates and re-estimates equation (3). Our results continue to be robust.

Overall, the empirical evidence from this section suggests that top pick stocks not only generate economically important and statistically significant abnormal returns, but they also outperform buy stock recommendations. Therefore, these findings are consistent with top picks, on average, reflecting analysts' genuinely best ideas and analysts possessing skill in identifying top picks.

6. Heterogeneity among Top Picks: Good and Bad Top Picks

Though top picks, on average, do not appear to be a manifestation of investment-banking related strategic forecasting behavior in the post-regulatory period, we examine in this section the heterogeneity in top pick stocks to better understand the motives underlying analysts' selection of top pick firms.

6.1 Characteristics of Good and Bad Top Pick Selections

To shed further light on whether some top picks are influenced by potential conflicts of interest, we identify best and worst top picks based on their ex post stock performance and examine how firm and forecasting characteristics vary across good and bad top pick selections. The fact that a top pick has poor investment performance could obviously be due to bad luck. Bad developments could occur at the top pick firm that the analyst could not possibly anticipate. However, if top picks are influenced by potential conflicts of interest, then the top picks with poor ex post investment performance, on average, should be more likely to be affected than the ones with good investment performance.

Specifically, we first rank each top pick annually based on its investment value relative to buy recommendations. Analyst *i's Top Pick j* is classified as a "*Good Top Pick*" in year *t* if the abnormal stock performance of *Top Pick j* (relative to buy rated stocks in analyst *i*'s portfolio in year *t*) falls under the highest quartile over its investment horizon compared to that of top picks by all analysts in year *t* for the same industry *j*. Abnormal stock outperformance accrued to a top pick designations and buy recommendations is measured with characteristics adjusted returns based on the calendar-time portfolio methodology used earlier. "*Bad Top Picks*" are identified analogously with the exception of having the lowest quartile ranking.[7]

To understand the characteristics of good and bad top picks, we re-estimate the logistic regressions introduced in Section 4, but now the dependent variable is a binary indicator that equals one if a stock is

[7] We also consider whether our results hold with alternative definitions of good and bad top picks including using top/bottom terciles and deciles (as opposed to quartiles) to identify good/bad top picks as well as using raw and risk-adjusted stock returns to measure stock outperformance (underperformance) of top picks (as opposed to DGTW) relative to buy recommendations. In each case, our inferences remain unchanged. Results are available from authors upon request.

designated as a *Good (*or *Bad) Top Pick* in year *t*. Model 1 of Table 7 in Panel A (B) compares the characteristics of good (bad) top picks to buy recommendations in the same industry-year, while Model 2 focuses on the differences between good/bad top picks and stocks with buy ratings by the same analyst in the same year.

Model 1 of Panel A finds that analysts expect higher EPS and target price implied stock returns for good top picks. In economic terms, a one standard deviation increase in relative EPS optimism (target price implied returns) increases the likelihood of a stock being classified as a *Good Top Pick* by 15.4% (14.94%) relative to buy recommendations. Contrary to the findings presented in Table 4, Model 1 of Panel A fails to find a statistically or economically important association between good top picks and investment banking affiliation. In Model 2, we compare good top picks to buy recommendations generated by the same analyst in the same year with the inclusion of analyst-year paired fixed effects and continue to find similar results. Other controls generally behave as in Table 4 — good top picks are more likely to be issued on larger firms with higher institutional ownership and lower uncertainty.

Panel B of Table 7 examines determinants of bad top picks. In sharp contrast to the results presented in Panel A, we find that underperforming top pick stocks are more likely to be affiliated with the investment banking arm of the top pick issuing analyst's brokerage house. Furthermore, analysts do not expect significantly higher EPS forecasts or target price implied returns for bad top pick selections relative to buy recommendations.

In sum, our results in this section help reconcile the evidence presented in Table 4 showing that top pick status is on average more likely to be designated on investment banking clients, potentially indicative of strategic forecasting behavior, and also more likely to be on stocks for which analysts anticipate higher EPS and target price implied stock performance, suggesting that on average top pick stocks are expected to perform well by analysts. The evidence in Table 7 illustrates that the subset of top picks that exhibit greatest outperformance are stocks that analysts are genuinely most optimistic about. In contrast, the subset of top picks exhibiting the worst future performance are stocks that are more likely to be investment banking affiliated stocks. We interpret these results as evidence that a subset of top picks might be more likely to perform poorly because they are chosen to further investment banking arms' interests rather than genuinely representing analysts' best ideas among their coverage universe. We therefore turn now to an investigation of whether the market and investors can distinguish between good and bad top picks to some extent.

6.2. Do Investors Distinguish between Good and Bad Top Picks?

In this section, we assess whether the financial markets can identify good and bad top picks when they are announced and whether investors trade good (bad) top picks more (less) actively.

6.2.1. Market Reaction

Our evidence up to this point suggests that top picks, on average, outperform buy recommendations; however, there exists a subset of underperforming top picks that are more likely to be generated on the basis of strategic considerations. Top pick implications for investors at least partly hinge on their ability to discern top picks reflecting strategic considerations from genuine best ideas of skilled analysts. In this section, we shift our attention to how the market and investors react to top picks and whether they distinguish between good and bad top picks.

As a starting point, we investigate whether the stock price reaction to the announcement of top picks differs between good and bad top picks. Towards this end, we distinguish between good and bad top picks where best (worst) top picks are, as before, those that exhibit the best (worst) ex post investment performance *excluding* the [0,+1] event window. We then compare cumulative CRSP VW-Index adjusted returns (i.e., CAR) over the [0,+1] event window surrounding the announcement of good and bad top picks. In untabulated analyses, we find that the [0,+1] event window CARs for good top picks is 2.37% with a *t*-statistic of 6.69. In contrast, the CAR for bad top picks is 0.55% with a *t*-statistic of 1.13 over the same event window. It follows from this that good top picks have a strong positive stock-price reaction while bad top picks have an insignificant stock price reaction. Not surprisingly, the difference between the abnormal announcement returns of good and bad top picks is significant at the 1% level. Consequently, the market appears capable of distinguishing between top picks when they are announced in such a way that the top picks that generate insignificant market reactions are the ones that subsequently have poor investment performance.

Next, we compare the market reaction to the announcement of good and bad top picks to that of buy recommendations in a multivariate setting. Towards this end, Table 8 re-estimates equation (3) using the cumulative abnormal CRSP VW-Index adjusted returns for the [0, +1] event window surrounding top pick and recommendation announcements as our dependent variable. Model 1 documents that market reactions to top picks are higher than market reactions to buy recommendations. This means that the announcement of top pick designations has an economically important and incremental price impact on stocks that already have a buy recommendation. Economically, top picks announcements generate 0.31% (0.21%) higher CARs over the two days surrounding the announcement window relative to buy recommendations announced in the same industry (by the same analyst) during the same year. To put this result in perspective, the market reaction to the announcement of buy recommendations by All-star analysts (analysts from Top 10 brokers) is 0.20% (0.32%) higher than the reaction to buy recommendations by non-stars (analysts from non-top 10 brokers). Therefore, the financial markets seem to place greater emphasis on top picks when they are announced and this association is economically important.

In Models 3 to 6, we distinguish between good and bad top picks. Our results from Models 3 and 4 suggest that market reactions to good top picks are higher relative to buy recommendations. More importantly, the market reaction to good top picks in Model 3 is higher than the market reaction to top picks in general in Model 1 by 0.63 percentage points. When we focus on bad top picks, however, we find that the market reaction to bad top pick announcements is *lower* compared to buy recommendations. For instance, Model 5 (6) indicates that the market reaction to a bad top pick announcement is roughly 1.20% (0.66%) lower compared to buy recommendations in the same industry-year (by the same analyst-year). Other control variables generally behave as expected. For instance, recommendations by analysts with higher general and firm specific forecasting experience, All-star status and those working at top 10 brokers generate higher market reactions.

Overall, the evidence from this section is consistent with the logic that financial market participants, on average, react more strongly to the announcement of top picks compared to stock recommendations and are also able to distinguish between good and bad top picks.

6.2.2. Institutional vs. Retail Trading Behavior

In light of the evidence provided in section 6.2.1, we next distinguish among financial market participants and investigate whether the trading behavior of institutional and retail investors exhibits asymmetries with respect to top picks as well as good versus bad top picks

Institutional investors represent the most important constituency for analyst research. The academic literature examines whether institutions can sort through Wall-Street research and discern good and bad stock recommendations; however, the evidence is mixed at best. For example, Malmendier and Shanthikumar (2007), Mikhail, Walther and Willis (2007) and others suggest institutions only act upon good stock recommendations and ignore uninformative ones. Conversely, Busse, Green, and Jegadeesh (2012) fail to find evidence of these investors possessing superior skills to analyze and discern among stock recommendations.

Analysts' top picks provide a unique and important laboratory to isolate institutional investors' ability to distinguish among analyst research outputs at least for three reasons: i) top picks capture substantial attention from institutions relative to stock recommendations, ii) analysts typically present top picks to institutional investors and interact with them at broker-hosted "best idea" conferences in an attempt to further discuss and clarify the investment theses and conviction behind their calls so that institutions potentially devote more time to understand sell-side analysts' top picks relative to stock recommendations, iii) while top picks, on average, have the potential to generate significant abnormal stock returns, we show that top pick selections with ex post poor performance are forecastable. Given the efforts made by analysts and brokerage houses to communicate and explain their top picks to institutional investors, we expect institutional investors to trade actively when stocks are designated as top picks. Furthermore, if institutional investors can distinguish between good and bap top picks when they are announced, they are likely to trade more (less) actively when they believe that a top pick is a good (bad) top pick. To test this conjecture, we rely on 286 million daily equity transactions executed by 886 unique funds over 2000 to 2014 period obtained from *Ancerno Ltd.* We calculate total institutional trading imbalance (i.e., institutional buy trading volume minus sell trading volume) over the [0, +1] event window surrounding the announcement date of top picks and buy recommendations.[8] Next, we repeat equation (3) but with the total institutional trading imbalance serving as our dependent variable.

Models 1 and 2 of Table 9 show the institutional buy-sell trading imbalance is significantly higher for top picks relative to buy recommendations. Model 1 (2) shows top picks are associated with 1.13% (1.27%) higher institutional trading imbalance compared to buy recommendations generated in the same industry (by the same analyst) for the same year. Given the average outperformance of top picks shown in Section 5, evidence is suggestive of top picks being beneficial to institutional investors.

Next, we distinguish between good and bad top picks. In Model 3 and 4, we find that the institutional trading imbalance is significantly higher for good top picks relative to buy recommendations. The positive coefficient on *Good Top Pick* in Model 3 (4) suggests that the institutional buy-sell trading imbalance is roughly 2.99% (5.04%) higher over the two days surrounding the announcement of good top picks. These coefficient estimates are roughly 2.5 to 4 times higher in economic terms relative to those obtained on the full sample of top picks (Models 1 and 2). Therefore, institutional investors appear to be able to discern best top picks and trade them at a higher intensity relative to not only buy recommendations but also an average top pick.

Model 5 (6) shows bad top picks are associated with significantly lower institutional trading imbalance compared to buy recommendations. For instance, the negative coefficient on bad top picks in Models 5 and 6 suggest that institutional trading imbalance is 3.5% to 4.7% lower over the two-day event window around the announcement of bad top picks. These results are economically important given the mean value of institutional trading imbalance in our sample is 1.08%. Overall, the results from Section 6.2.2 provide strong empirical

[8] Untabulated analyses consider trading imbalance over the alternative windows [0, +2], [0, +3], [0, +4], and [0, +5]. Our inferences from Tables 9 and 10 remain similar. These results are available from authors based on request.

support for the notion that institutional investors are more likely to act upon top picks, however, they are capable of discerning among good and bad top picks of sell-side analysts.

Finally, we turn our attention to retail traders. Unlike institutional investors, retail traders are typically less sophisticated and often have a relationship only with one investment advisor or broker. As such, it is potentially more difficult and costlier for retail traders to distinguish between good and bad analyst research.[9] In our context, we examine whether retail investors take all top picks at face value or discern among good and top picks. Examining this association is particularly relevant given the SEC warning advising retail investors to "do their homework before investing" in a company solely because of its "top pick" status.[10]

We identify retail trading from daily Trade and Quote (TAQ) data as in Boehmer, Jones, Zhang and Zhang (2019), Bushee, Cedergren and Michels (2020), and others. These papers take advantage of two institutional features of retail trading: i) the majority of stock trades by retail investors take place off-exchange (filled from broker's investors or sold to wholesalers) and are classified by TAQ using an exchange code "D", and ii) retail trades receive very small price improvements relative to the National Best Bid or Offer (ranging between 0.01 cents to 0.2 cents). Second, we identify transactions as retail purchases (sales) if a trade is executed just below (above) a round penny. To be conservative, we omit trades executed at a round penny or near half-penny. Finally, we define the retail order trading imbalance as the difference between retail purchases and sales for stock j at time t. We re-estimate equation (3) with total retail order imbalance over the [0, +1] event window serving as our dependent variable.

Consistent with the evidence presented for institutional investors, retail trades seem to exhibit more pronounced buying behavior around the announcement of top picks. For instance, the retail trading imbalance is 0.45% (1.57%) higher for top picks compared to buy recommendations in the same industry (by the same analyst). However, Table 10 suggests that retail investors cannot distinguish between good and bad top picks.

[9] This view is echoed by past academic research in the context of earnings surprises (Battalio and Mendenhall, 2005; Hirshleifer, Myers, Myers and Teoh, 2008) and stock recommendations (e.g. Malmendier and Shanthikumar, 2014).
[10] See SEC Investor Publication "Analyzing Analyst Recommendations", August 30, 2010.

Models 3 and 4 show that good top picks are associated with a *lower* retail trading imbalance relative to buy recommendations. In economic terms, the retail trading imbalance is roughly 1.5% to 1.8% *lower* following the announcement of good top picks relative to buy recommendations. Focusing on bad top picks, we likewise fail to find evidence that points to retail investors discerning bad top picks. In particular, unlike institutional investors, Models 5 and 6 show that the trading imbalance is not significantly lower for bad top picks relative to buy recommendations. Therefore, the trading on top picks by retail investors is mostly driven by top picks with relatively average ex post investment performance and these investors do not appear to discern between good and bad top picks.

7. Career and Reputational Consequences of Good and Bad Top Picks

So far, we have provided evidence that top pick designations receive significant attention from retail and institutional investors and the financial press, and that top picks outperform stock recommendations, on average. However, we also saw that not all top picks outperform, that bad top picks are more likely to be motivated by strategic bias than other top picks, and that institutional investors seem to be able to distinguish good top picks from bad ones. The obvious question is whether analysts who make bad picks suffer from doing so. Further, the attention-grabbing nature of top picks, coupled with these research outputs representing analysts' single best ideas, suggests that market participants are likely to infer an analyst's forecasting skill from the performance of their top picks. As such, we expect bad top picks to affect an analyst's career adversely and good top picks to help it. Further, it seems likely that bad top picks would reduce an analyst's credibility with investors, so that her future stock recommendations would receive less weight from them.

We first investigate whether analyst career outcomes relate to top picks. Analyst i is classified as a "*Good Top Picker*" if she is associated with a good top pick selection in year t as defined in Section 6.1."*Bad Top Picker*" analysts are identified analogously with the exception of being associated with a bad top pick selection in year t. Following the literature (Mikhail, Walther, and Willis, 1999; Hong, Kubik, and Solomon, 2000; Hong and Kubik, 2003), we assume an analyst experiences a positive career advancement if she moves from a lower status broker to a higher status one. Conversely, a negative career move is defined as moving from a higher to a lower status brokerage house. We follow Hong, Kubik, and Solomon (2000) and use the number of analysts employed by a broker *k* in year *t* to define high versus low status. An analyst movement is defined as a promotion if analyst *i* moves from a non-top 10 decile broker to a top 10 decile broker in year *t*+1.[11] Because analysts working for the highest decile brokers cannot move up, they are excluded from the analyses focusing on promotions. In a similar vein, an analyst move is defined as a demotion if analyst *i* moves from a top 10 broker to a non-top 10 broker in year *t*+1. If analyst *i* stops producing research in year *t*+1, we classify this analyst as having left the profession and exclude such analysts from promotion and demotion analyses.[12] Next, we estimate logistic regressions with a binary dependent variable that equals one if analyst *i* experiences demotion (or promotion) in year *t*+1, zero otherwise. The primary variables of interest are binary indicators that represent whether an analyst *i* designated a stock as a top pick in year *t* (*Top Pick Analyst*) and issued an over or underperforming top Pick (*Good/Bad Top Picker)* in year *t*, and zero otherwise. We further include a comprehensive set of analyst specific characteristics introduced in equation (1) along with an independent variable that captures the average investment value of buy recommendations issued by analyst *i* at year *t* (*Average Buy Rec Ret)*. Standard errors are heteroskedasticity-consistent and double-clustered at the analyst and year levels. Formally, our econometric model (omitting time and analyst subscript) is as follows:

$$(\mathit{Demotion/Promotion}=1) = \beta_1\, \mathit{Top\ Pick\ Analyst/Bad\ Top\ Picker/Good\ Top\ Picker} + \beta_2\, \mathit{Average\ Size\ in\ Portfolio} + \beta_3\, \mathit{Average\ BM\ in\ Portfolio} + \beta_4\, \mathit{Gexp} + \beta_5\, \mathit{Average\ Fexp} + \beta_6\, \mathit{Portfolio\ Size} + \beta_7\, \mathit{Portfolio\ Gics}$$

[11] Further analyses consider a multinomial ordered logit model with three levels of dependent variable (1=promotion, 0=no job change, -1=demotion) and find consistent results. We also re-define analyst promotions or demotions based on movements from a lower to higher decile brokerage house and uncover robust results. However, one important shortcoming is that it is not completely clear whether an analyst move from a 7th decile broker to an 8th decile broker represents a significant promotion or if an 8th decile to 7th decile move represents a significant demotion.

[12] The evidence on analysts leaving the profession is mixed: Hong, Kubik and Solomon (2000) and Hong and Kubik (2003) argue that sell-side analysts leaving the profession are unlikely to obtain better jobs. Using hand-collected data from LinkedIn, Cen, Ornthanalai, Schiller (2011) find that 40% of analysts exiting sell-side research find immediate employment at buy-side institutions. Therefore, analysts who stop producing research at year *t*+1 are excluded from our analyses on demotions/promotions.

$$+ \beta_8 \textit{ Broker Ind. specialization} + \beta_9 \textit{ All-Star (t-1)} + \beta_{10} \textit{ Average Buy Rec Return} + \beta_{11} \textit{ Investment Bank Affiliation} + \beta_{12} \textit{ Average Relative EPS Optimism} + \beta_{13} \textit{ Average Report count} + \beta_{14} \textit{ Average Drop Coverage} + \beta_{15} \textit{ Average PMAFE} + \beta_{16} \textit{ Average Institutional Holding in Portfolio} + \beta_{17} \textit{ Average Turnover in Portfolio} + \beta_{18} \textit{ Average Dispersion in Portfolio} + \textit{Year Fixed Effects} + \varepsilon \quad (4)$$

Panel A of Table 11 presents results for demotions and shows top-pick-issuing analysts do not have significantly different rates of demotion compared to other analysts. Distinguishing among analysts based on the performance of their top picks, Model 2 of Panel A shows that bad top pickers are associated with an increased likelihood of demotion in the following year. Economically, the likelihood of demotion is roughly two times higher for analysts issuing bad top picks. To put this finding in perspective, all-star analysts are 55% less likely to be demoted. In contrast, the coefficient estimate on *Good Top Picker* implies that such analysts have a lower propensity to be demoted (albeit statistically insignificant). Interestingly, we fail to find evidence that negative career developments are related to the investment value of buy recommendations. In Models 3 and 4, we re-estimate logistic regressions after focusing only on a subset of analysts moving across brokers (i.e. exclude analysts who do not change jobs at year t+1). Our results continue to illustrate that bad top picks translate into negative career moves (t-statistic of 3.31). Further, analysts identifying good top picks are significantly less likely to be demoted (t-statistic of 2.35). Models 5-8 of Panel B in Table 11 fail to find any significant association between the issuance or performance of top picks and analysts moving up to higher status brokers. Therefore, it appears there are asymmetric career consequences to top picks, and rewards and punishments for identifying good and bad top pick stocks seem to be confined to demotions.

As an alternative way of investigating career implications of top picks, we further consider analysts' election to the Institutional Investor All-Star team roster. To the extent that institutional investors pay attention to top picks, they may also consider top picks' performance when they cast votes for All-star analysts. Anecdotal evidence also corroborates this view – narratives accompanying All-star analysts' profiles in the October issue of Institutional Investor Magazine (IIM) explicitly focuses on institutional investors' discussions of elected analysts' top picks. To test this question, Table 12 re-estimates equation (4) with the dependent variable taking the form of a binary variable that equals one if the analyst is selected to the all-star roster in year t+1*,* zero otherwise. Model 1 shows top-pick issuing analysts are, on average, more likely to be named to IIM's All-Star team. In Model 2, we find good top picks positively influence an analyst's odds of being selected into the All-Star roster. The odds of becoming an all-star analyst are 107% incrementally higher for good top pickers after explicitly controlling for other factors documented in the literature. Similarly, bad top pickers are associated with a lower probability of becoming an All-star. The coefficient on Bad Top Pickers is economically important, however, it lacks statistical significance at conventional levels (t-statistic of 0.89).

Top picks are highly publicized in the financial markets. While a good top pick may help an analyst gain reputation, a bad top pick may result in reputational loss. If so, the investment value of top picks may affect investors' perception of a sell-side analyst's forecasting skill, resulting in stronger (weaker) market reactions to the *same* analyst's research on *non-top pick* firms. Note that this spillover is conditional on investors evaluating top picks and extrapolating an analyst's stock picking skill based on the performance of her best ideas. To shed light on this conjecture, Table 13 examines the association between top picks and the stock price reaction to recommendation revisions generated by the same analyst. Because analyst upgrades and downgrades convey opposite signals, Models 1-4 focus on recommendation upgrades while Models 5-8 repeat the analysis for downgrades.

In Models 1 and 5, we do not find evidence that top-pick-issuing analysts are associated with greater price impact for upgrades or downgrades. However, Models 2 and 6 provide suggestive evidence of reputational consequences of top picks for analysts. Stock market reactions to recommendation upgrades (downgrades) are 73 (92) basis points lower (higher) for bad top-pick issuing analysts after controlling for a battery of analyst, firm and broker specific characteristics along with the direction and magnitude of underlying recommendation revision. Other controls generally have expected signs—recommendation revisions by all-star analysts elicit more pronounced market reactions, so do revisions from analysts employed at larger brokerage houses.

Interestingly, while signed correctly, good top picks do not appear to translate into statistically significant reputational gains.

Overall, the evidence points to bad top picks being costly to sell-side analysts' careers in the form of demotions and reputational loss with investors, while good top picks are rewarded through promotions to higher status brokers and selections into IIM's All-star roster. These findings help us improve our understanding of how analysts gain and lose reputational capital in the labor and financial markets.

8. Conclusion

In this paper, we show that analysts make frequent use of the top pick designation after the regulatory changes and the Global Analyst Research Settlement of 2002. Shortly after the regulatory changes, many brokerage houses move to a three-tier rating system that reduces the granularity of the information provided to investors compared to the five-tier system prevalent before 2002. The top pick designation enables analysts to provide greater granularity of information to investors within the three-tier rating system. It is used to highlight the stock about which analysts have the highest conviction of best performance. We find that, on average, this designation has investment value for investors. It is also a designation that attracts much interest from institutional and retail investors as well as from the media. This level of attention may not be surprising since brokerages invest resources to publicize their top picks both through the media and through broker-hosted top pick conferences. We show that both institutional investors and retail investors trade in response to a stock receiving such designation.

The obvious issue with granularity of information is that it makes it possible for analysts to draw attention to specific stocks in a way that can be highly valuable to the firms that receive that attention. Analysts might therefore be tempted to use top designation to pursue objectives other than giving the best investment advice to investors. The three-tier system is largely viewed as a way to reduce the value of this discretion for analysts. Absent the temptation of analysts to use a valuable designation to pursue objectives that are not in the interest of investors, greater granularity is generally valuable to investors – at least up to a point. We investigate whether analysts use the top pick designation strategically. We find that on average they do not in that investors gain from following their advice. Not all top picks have superior investment performance. When we focus on the top picks with poor investment performance, we find that they are more likely to be designated for companies that are investment banking clients. However, the market is not fooled by potentially strategic top pick choices. The market reacts favorably to top pick designations in general, but not to those that are subsequently followed by poor performance. We also find that top pick designations that subsequently have poor investment performance affect institutional investors' trading less when they are announced. Finally, we find that analysts who have poor top pick designations suffer career consequences and their credibility is hurt. These findings suggest that the use of top pick designations help investors on average and that the marketplace disciplines analysts issuing bad top picks.

References:

Ahn, Minkwan, Michael Drake, Hangsoo Kyung, and Han Stice, 2019. "The role of the business press in the pricing of analysts' recommendation revisions." *Review of Accounting Studies* 24: 341-392.

Altınkılıç, Oya, Robert S. Hansen, and Liyu Ye, 2016. "Can analysts pick stocks for the long-run?" *Journal of Financial Economics* 119: 371-398.

Asquith, Paul, Michael B. Mikhail, and Andrea S. Au, 2005. "Information content of equity analyst reports." *Journal of Financial Economics* 75: 245-282.

Bae, Kee-Hong, René M. Stulz, and Hongping Tan, 2008. "Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts." *Journal of Financial Economics* 88: 581-606.

Barber, Brad M., and Terrance Odean, 2008. "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors." *The Review of Financial Studies* 21: 785-818.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001. "Can investors profit from the prophets? Security analyst recommendations and stock returns." *The Journal of Finance* 56: 531-563.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2006. "Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations." *Journal of Accounting and Economics* 41: 87-117.

Battalio, Robert H., and Richard R. Mendenhall. "Earnings expectations, investor trade size, and anomalous returns around earnings announcements." *Journal of Financial Economics* 77: 289-319.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen, 2017. "It depends on where you search: Institutional investor attention and underreaction to news." *The Review of Financial Studies* 30: 3009-3047.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang, 2019. "Tracking retail investor activity." Unpublished working paper.

Boni, Leslie, and Kent L. Womack, 2006. "Analysts, industries, and price momentum." *Journal of Financial and Quantitative Analysis* 41: 85-109.

Bonner, Sarah E., Artur Hugon, and Beverly R. Walther, 2007. "Investor reaction to celebrity analysts: The case of earnings forecast revisions." *Journal of Accounting Research* 45: 481-513.

Boulland, Romain, Chayawat Ornthanalai, and Kent L. Womack, 2017. "Speed and Expertise in Stock Picking: Older, Slower, and Wiser?" Unpublished working paper.

Bushee, Brian, Matthew Cedergren, and Jeremy Michels, 2020. "Does the media help or hurt retail investors during the IPO quiet period?" *Journal of Accounting and Economics* 69: 1-19.

Busse, Jeffrey A., T. Clifton Green, and Narasimhan Jegadeesh, 2012. "Buy-side trades and sell-side recommendations: Interactions and information content." *Journal of Financial Markets* 15: 207-232.

Carhart, M.M., 1997. "On persistence in mutual fund performance." *The Journal of Finance* 52: 57-82.

Cen, Ling, Chayawat Ornthanalai, and Christoph M. Schiller, 2017. "Navigating wall street: Career concerns and analyst transitions from sell-side to buy-side." Unpublished working paper.

Clarke, Jonathan E., Ajay Khorana, Ajay Patel, and P. Raghavendra Rau, 2011. "Independents’ day? Analyst behavior surrounding the Global Settlement." *Annals of Finance* 7: 529-547.

Clement, Michael B., 1999. "Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?" *Journal of Accounting and Economics* 27: 285-303.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010. "Sell-side school ties." *The Journal of Finance* 65: 1409-1437.

Corwin, Shane A., Stephannie A. Larocque, and Mike A. Stegemoller, 2017. "Investment banking relationships and analyst affiliation bias: The impact of the global settlement on sanctioned and non-sanctioned banks." *Journal of Financial Economics* 124: 614-631.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011. "In search of attention." *The Journal of Finance* 66: 1461-1499

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997. "Measuring mutual fund performance with characteristic-based benchmarks." *The Journal of Finance* 52: 1035-1058.

Fama, Eugene F., and R. Kenneth. French, 1993. “Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics* 33: 3-56.

Focke, Florens, Stefan Ruenzi, and Michael Ungeheuer, 2020. "Advertising, attention, and financial markets." *The Review of Financial Studies* 33: 4676-4720.

Gibbons, Brian, Peter Iliev, and Jonathan Kalodimos, 2020. "Analyst information acquisition via EDGAR." *Management Science*, forthcoming.

Hirshleifer, David A., James N. Myers, Linda A. Myers, and Siew Hong Teoh, 2008. "Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades." *The Accounting Review* 83: 1521-1550.

Hong, Harrison, Jeffrey D. Kubik, and Amit Solomon, 2000. "Security analysts' career concerns and herding of earnings forecasts." *The Rand Journal of Economics* 31: 121-144.

Hong, Harrison, and Jeffrey D. Kubik, 2003. "Analyzing the analysts: Career concerns and biased earnings forecasts." *The Journal of Finance* 58: 313-351.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2008. "Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations." *The Review of Financial Studies* 22: 4189-4217.

Loh, Roger K., and René M. Stulz, 2011. "When are analyst recommendation changes influential?" *The Review of Financial Studies* 24: 593-627.

Loh, Roger K., and René M. Stulz, 2018. "Is sell-side research more valuable in bad times?" *The Journal of Finance* 73: 959-1013.

Malmendier, Ulrike, and Devin Shanthikumar, 2007. "Are small investors naive about incentives?" *Journal of Financial Economics* 85: 457-489.

Malmendier, Ulrike, and Devin Shanthikumar, 2014. "Do security analysts speak in two tongues?" *The Review of Financial Studies* 27: 1287-1322.

Mehran, Hamid, and René M. Stulz, 2007. "The economics of conflicts of interest in financial institutions." *Journal of Financial Economics* 85: 267-296.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999. "Does forecast accuracy matter to security analysts?" *The Accounting Review* 74: 185-200.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 2007. "When security analysts talk, who listens?" *The Accounting Review* 82: 1227-1253.

Pástor, Ľuboš, and Robert F. Stambaugh, 2003. "Liquidity risk and expected stock returns." *Journal of Political Economy* 111: 642-685.

Stickel, Scott E., 1992. "Reputation and performance among security analysts." *The Journal of Finance* 47: 1811-1836.

Tetlock, Paul C., 2010. "Does public financial news resolve asymmetric information?" *The Review of Financial Studies* 23: 3520-3557.

Appendix A. Variable Descriptions

Variable	Definition
Top Pick	Indicator variable is one if analyst *i* assigns a top pick designation to stock *j* at time *t*, and zero otherwise. Information on Top Picks is manually obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.*
GSVI	Google Search Volume Index (GSVI) over the [0, +5] event window surrounding the announcement of analyst research on stock *j*. GSVI data is from 2004 to 2016 on S&P 500 firms.
AGSVI	Abnormal Google Search Volume Index (AGSVI) over the [0, +5] event window surrounding the announcement of analyst research on stock *j* calculated as GSVI minus the median value of GSVI over eight weeks preceding the announcement of a corresponding analyst research. GSVI data is from 2004 to 2016 on S&P 500 firms.
Bloomberg Search	Search activity on Bloomberg terminals over the [0, +5] event window surrounding the announcement of analyst research on stock *j*. Bloomberg scores of 0, 1, 2, 3 or 4 are transformed to continuous values with Bloomberg search scores taking the value of -0.350, 1.045, 1.409, 1.647 and 2.154, respectively. Bloomberg search activity data is from February 2010 to December 2016 on S&P 500 firms
% Financial Press Coverage	% of top picks/stock recommendations with financial media articles published on days [0, +5] relative to the announcement of analyst research. Financial media coverage data is from *RavenPack's Dow Jones Edition* that includes financial press articles from *Dow Jones Newswire* and *The Wall Street Journal*
# Financial Press Articles	Number of financial media articles published on top picks/stock recommendations [0, +5] event window relative to the announcement of analyst research. Financial media coverage data is from *RavenPack's Dow Jones Edition* that includes financial press articles from *Dow Jones Newswire* and *The Wall Street Journal*
Strong Buy	Indicator variable is one if a stock *j* is rated as Strong buy at time *t*, zero otherwise.
Size	The natural log of market capitalization (Size) of firm *j* at time *t*-1. Information on Size is obtained *from CRSP.*
BM	The natural log of Book to Market (BM) ratio calculated as book value of total equity dividend by market value of total equity for firm *j* at time *t*-1. Information on BM *is* obtained from *CRSP/Compustat.*
Institutional Holding	The natural log of total % Institutional ownership of for firm *j* at time *t-1* as reported by WRDS.
Turnover	The natural log of the average stock daily turnover (i.e., share volume scaled by shares outstanding) over the past twelve-months for firm *j* at time *t.* Information on Turnover is obtained from *CRSP.*
SSA Coverage	The number of sell-side analysts covering firm *j* at time *t-1* as reported by I/B/E/S.
Idiosyncratic Volatility	The natural log of the standard deviation of residuals from a daily time-series regression of past twelve-month firm returns against market returns and Fama-French Size and BM factors for firm *j* at time *t*
Dispersion	Earnings forecast dispersion of past twelve-month for firm *j* at time *t* as reported by I/B/E/S.

Past 12-m return	CRSP Value Weighted-index-adjusted buy-and hold abnormal returns over 12 months for firm *j* at time *t*.
Fexp	The total number of years that analyst *i* has covered firm *j* at time *t in* I/B/E/S.
Gexp	The total number of years that analyst *i* has appeared in I/B/E/S at time *t*.
Portfolio size	The number of firms followed by analyst *i* at time *t* as reported by I/B/E/S.
Portfolio Gics	The number of 4 digit GICS industries followed by analyst *i* at time *t* as reported by I/B/E/S.
Relative EPS Optimism	Indicator variable is one if analyst *i*'s current earnings forecast on firm *j* is more optimistic than the median consensus earnings forecast for firm *j* at time *t (*as reported by I/B/E/S), zero otherwise.
All-star	Indicator variable is one if analyst *i* is named to *Institutional Investor's* All-star team at time *t*, and zero otherwise. Information on All-star analysts are retrieved from *Institutional Investor Magazine.*
Drop Coverage	Indicator variable is one if analyst *i* dropped coverage of firm *j* at time *t*+1 as reported by I/B/E/S, zero otherwise
Top 10	Indicator variable is one if analyst works for a top decile brokerage house (*Top10*) at time *t* where broker size is calculated based on the number of employed analysts. Information on brokerage houses are retrieved from I/B/E/S.
Investment Bank Affiliation	Indicator variable is one if investment banking arm of analyst *i*'s brokerage house was the underwriter of firm *j*'s Initial Public offering (IPO)/seasoned equity offering (SEO) over the past two years, zero otherwise. Information on IPO and SEOs are obtained from SDC Platinum.
Broker Ind Specialization	Percentage of analysts following firm *j*'s 4 digit GICS industry *k* from analyst *i*'s broker at time *t* as reported by I/B/E/S
% Target Price Implied Return	Implied 12 month buy and hold return based on the 12 month price target issued by analyst *i* on stock *j* at time t as reported by I/B/E/S.
Target Price Implied Return Rank	The relative rank of stock *j*'s target price implied return (*% Target Price Implied Return*) among all buy rated stocks by analyst *i* at time *t*
Good Top Pick	Analyst *i's* Top pick *j* is classified as a "*Good Top Pick*" at year *t* if the abnormal stock performance of *Top pick j* (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the *highest* quartile over its investment horizon compared to that of top picks by all analysts at year *t* for the same industry *j*. Abnormal stock outperformance is defined with DGTW characteristics adjusted returns accrued to a top pick and buy recommendation based on calendar-time portfolio methodology.
Bad Top Pick	Analyst *i's* Top pick *j* is classified as a "*Bad Top Pick*" at year *t* if the abnormal stock performance of Top pick *j* (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the *lowest* quartile over its investment horizon compared to that of top picks by all analysts at year *t* for the same industry *j*. Abnormal stock outperformance is defined with DGTW characteristics adjusted returns accrued to a top pick and buy recommendation based on calendar-time portfolio methodology.
Good Top Picker	Indicator variable is one if analyst *i* is associated with a "*Good Top Pick*" at year *t,* zero otherwise.
Bad Top Picker	Indicator variable is one if analyst *i* is associated with a "*Bad Top Pick*" at year *t,* zero otherwise.
Average Buy Rec return	The average calendar-time portfolio DGTW adjusted investment returns accrued to buy recommendations issued by analyst *i* at year *t*.

Analyst reports count	Number of all forecasts issued by analyst *i* on firm *j* in time *t* as reported by I/B/E/S.
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (*AFE*) for analyst *i* on firm *j* at time *t* and the mean absolute forecast error (*MAFE*) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. Earnings forecasts are retrieved from I/B/E/S.
Revision	The magnitude of recommendation revision on stock *j* by analyst *i* at time *t* from previous recommendation level on stock *j* by analyst *i*.

Table 1. Sample Statistics

This table reports sample summary statistics over 1999-2016. Panel A presents summary statistics for the distribution of brokerage houses adopting 3-tier rating scales, stock coverage, and buy rated stocks from 3-tier brokerage houses. Panel B presents the distribution of top picks, number of brokerage houses issuing top picks, % of top picks generated by 3-tier brokers and % of buy rated stocks identified as a top pick at brokers with 3-tier rating scales. Panel C reports the distribution of top pick announcements across months. Panel D tabulates % overlap between the announcement of top picks and stock recommendations at I/B/E/S. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions.

Panel A. Distribution of 3-tier Brokerage houses

Year	No of Brokers with 3 Tier Ratings	% of IBES Brokers with 3 Tier Ratings	% of IBES Stocks covered by Brokers with 3 Tier Ratings	% Buy Rated Stocks at Brokers with 3 Tier Ratings
1999	104	35.99%	13.42%	75.10%
2000	103	35.52%	14.58%	73.01%
2001	79	31.60%	14.60%	68.06%
2002	89	34.90%	10.26%	63.60%
2003	195	61.13%	59.68%	50.47%
2004	235	66.76%	77.80%	51.03%
2005	237	67.14%	74.44%	52.58%
2006	232	71.17%	79.21%	50.87%
2007	222	72.79%	83.48%	54.83%
2008	229	74.84%	76.09%	51.61%
2009	238	73.68%	79.57%	52.12%
2010	282	80.11%	83.59%	57.20%
2011	250	78.37%	76.96%	58.05%
2012	247	76.71%	79.04%	53.11%
2013	228	73.55%	78.70%	53.04%
2014	249	78.55%	86.30%	57.95%
2015	259	81.45%	88.81%	54.93%
2016	231	75.24%	88.23%	49.38%

Panel B. Distribution of Top Picks

Year	No of Top Picks (N=3563)	No of Brokers issuing Top Picks	% of Top Picks by Brokers with 3 Tier Ratings	% Top Picks as of Buy Rated Stocks at Brokers with 3 Tier Ratings
1999	3	1	0.00%	0.00%
2000	5	3	0.00%	0.01%
2001	9	4	33.33%	0.04%
2002	29	10	72.41%	0.03%
2003	49	18	83.67%	0.16%
2004	128	32	93.75%	0.35%
2005	200	26	95.50%	0.36%
2006	193	29	88.08%	0.45%
2007	249	35	93.98%	0.78%
2008	196	30	94.90%	1.86%
2009	158	36	96.20%	0.50%
2010	240	43	98.75%	0.69%
2011	423	44	98.35%	1.36%
2012	376	44	96.54%	1.71%
2013	307	41	97.39%	1.42%
2014	330	53	97.88%	1.43%
2015	343	45	99.71%	1.26%
2016	325	47	98.46%	1.81%

Panel C: % Overlap between Top Pick and Stock Recommendation Announcement

Top Pick Coincides with Stock Coverage Initiations	Top Pick Coincides with Recommendation Upgrade	Top Pick Coincides with Recommendation Reiteration	Top Pick does not Coincide with any Recommendation Announcement
14.70%	3.54%	3.90%	81.13%

Panel D: Distribution of Top Pick Announcements Across Months

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
35.44%	15.59%	5.96%	4.30%	2.96%	3.31%	2.75%	1.87%	2.01%	3.21%	5.99%	16.61%

Table 2. Top Picks and Financial Market Attention: Retail vs Institutional Investors

This table presents average retail and institutional attention over (0, +5) event window following the announcement of top picks vs all buy recommendations issued i) in the same industry at the same year (i.e., industry-year matched) in Panel A, ii) by the same analysts at the same year (i.e., analyst-year matched) in Panel B. Panel C reports OLS regressions of average retail and institutional attention across top picks and buy recommendations. Retail attention is measured by average Google Search Volume Index (GSVI) and obtained from Google Trends from 2004 to 2016 for S&P 500 firms. Abcnormal retail attention (Abnormal GSVI) subtracts the median value of GSVI over eight weeks preceding the announcement of a corresponding analyst research output from GSVI. Institutional attention is measured by institutional investors' search activity in Bloomberg terminals over 2011-2016 for S&P 500 firms. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Top picks vs Buy Recommendations (Industry-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
Mean GSVI [0, +5]	53.944***	46.176***	7.769***
	(66.62)	(126.80)	(8.91)
Mean Abnormal GSVI [0, +5]	6.797***	0.779***	6.019***
	(14.36)	(10.30)	(12.70)
Mean Bloomberg Search [0, +5]	1.135***	0.682***	0.453***
	(37.10)	(67.10)	(14.95)

Panel B: Top picks vs Buy Recommendations (Analyst-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
Mean GSVI [0, +5]	54.538***	46.455***	8.084***
	(46.32)	(41.83)	(5.21)
Mean Abnormal GSVI [0, +5]	5.949***	0.448	5.501***
	(10.17)	0.76)	(6.80)
Mean Bloomberg Search [0, +5]	1.130***	0.707***	0.406***
	(34.97)	(18.39)	(6.33)

Panel C. Top picks vs Buy Recommendations: Multivariate Analyses

	Top Picks vs Buy Recommendations (Industry-year matched)			Top Picks vs Buy Recommendations (Analyst-year matched)		
	GSVI	Abnormal GSVI	Bloomberg Search	GSVI	Abnormal GSVI	Bloomberg Search
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	732.057***	631.538***	43.925***	766.787***	629.416***	42.856***
	(5.666)	(7.552)	(13.652)	(6.051)	(7.820)	(10.141)
Strong Buy	19.248	94.813	-3.116			
	(0.126)	(0.957)	(-1.256)			
Size	-51.621	3.978	23.001***	88.089	30.416	23.519***
	(-0.824)	(0.098)	(23.719)	(0.794)	(0.431)	(8.834)
BM	-642.075***	-251.122**	6.931**	4.484	-255.013	12.174
	(-4.068)	(-2.458)	(2.296)	(0.017)	(-1.524)	(1.458)
Institutional holding	-2780.044***	433.581	-21.079*	-1364.429	238.049	-0.763
	(-3.988)	(0.960)	(-1.737)	(-1.146)	(0.315)	(-0.023)
Turnover	88.285	-82.241	12.837***	134.722	86.016	26.422***
	(0.733)	(-1.054)	(6.185)	(0.618)	(0.621)	(4.506)
SSA coverage	-11.725**	1.244	0.389***	-21.218**	3.100	0.454*
	(-2.030)	(0.333)	(4.290)	(-2.201)	(0.506)	(1.791)
Idiosyncratic Volatility	-363.141*	131.415	16.342***	-215.045	173.769	-14.497
	(-1.819)	(1.016)	(5.111)	(-0.608)	(0.772)	(-1.553)
Dispersion	14199.249***	7823.525***	579.643***	9161.738**	8772.970***	538.898**
	(4.445)	(3.784)	(5.409)	(1.970)	(2.970)	(2.252)
Past 12-m return	-0.942	155.800**	0.004	-100.853	98.734	0.809
	(-0.813)	(2.076)	(0.193)	(-0.514)	(0.791)	(0.137)
Fexp	90.675***	0.103	0.376**	1.051***	0.023	0.010**
	(7.197)	(1.268)	(1.968)	(5.177)	(0.180)	(1.971)
Gexp	-32.602	-8.737	-0.085			
	(-0.956)	(-0.396)	(-0.604)			
Portfolio size	-16.930	-7.824	-0.169*			
	(-1.497)	(-1.069)	(-1.896)			
Portfolio Gics	86.056	45.744	-0.826**			
	(1.593)	(1.308)	(-2.459)			
Relative EPS Optimism	154.400*	97.392*	1.807	311.339**	139.830	6.262
	(1.835)	(1.786)	(1.115)	(2.104)	(1.487)	(1.517)
All-star	-265.633	108.695	0.993			
	(-1.140)	(0.721)	(0.452)			
Drop Coverage	18.594	1.190	0.474	372.055	367.581	-7.794
	(0.113)	(0.011)	(0.216)	(0.991)	(1.541)	(-0.721)
Top 10	318.148**	99.628	-0.035	600.140	-41.031	-18.391
	(1.987)	(0.959)	(-0.024)	(1.053)	(-0.113)	(-1.218)
Investment Bank Affiliation	-5.202**	-132.931	-0.053	-596.075*	-543.836**	-25.315*
	(-2.535)	(-0.998)	(-0.937)	(-1.753)	(-2.495)	(-1.935)

Broker Ind Specialization	257.190	1.079	-0.828	7.641*	5.705**	-0.013
	(1.339)	(0.867)	(-0.389)	(1.747)	(2.053)	(-0.112)
Industry-Year Fixed Effects	Y	Y	Y	N	N	N
Analyst-Year Fixed Effects	N	N	N	Y	Y	Y
R^2	72.78%	65.32%	25.34%	68.59%	60.79%	74.38%
N	11,678	11,673	9,016	3,147	3,145	3,434

Table 3. Top Picks and Financial Press Coverage

This table presents average % financial press coverage and number of press articles over [0, +5] event window following the announcement of top picks vs all buy recommendations issued i) in the same industry at the same year (i.e., industry-year matched) in Panel A, ii) by the same analysts at the same year (i.e., analyst-year matched) in Panel B. Panel C reports OLS regressions of average press coverage across top picks and buy recommendations. Financial press coverage data are from *RavenPack's Dow Jones Edition* that includes news articles from *Dow Jones Newswire* and *The Wall Street Journal* over 1999 and 2016. Financial press articles' headlines are manually checked to ensure press articles belong to a corresponding analyst research. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Top picks vs Stock Recommendations (Industry-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
% Financial press coverage [0, +5]	0.477***	0.245***	0.232***
	(53.46)	(86.70)	(28.08)
# Financial press articles [0, +5]	1.954***	0.656***	1.297***
	(29.16)	(69.57)	(19.90)

Panel B: Top picks vs Buy Recommendations (Analyst-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
% Financial press coverage [0, +5]	0.476***	0.303***	0.173***
	(52.94)	(49.79)	(17.35)
# Financial press articles [0, +5]	1.950***	0.864***	1.086***
	(28.82)	(28.64)	(15.21)

Panel C. Top picks vs Buy Recommendations: Multivariate Analyses

	Top Picks vs Buy Recommendations (Industry-year matched)	Top Picks vs Buy Recommendations (Analyst-year matched)
	Model 1	Model 2
Top Pick	114.644***	110.652***
	(25.884)	(20.303)
Strong Buy	4.702***	
	(2.720)	
Size	4.321***	8.444***
	(6.927)	(5.248)
BM	-4.808***	5.822
	(-2.950)	(1.521)
Institutional holding	-30.578***	-20.535
	(-5.565)	(-1.478)
Turnover	-1.510	-2.776
	(-1.518)	(-1.137)
SSA coverage	2.378***	2.198***
	(30.816)	(11.218)
Idiosyncratic Volatility	15.320***	18.804***
	(7.505)	(3.748)
Dispersion	-14.189*	-5.030
	(-1.670)	(-0.201)
Past 12-m return	10.492***	12.287***
	(10.144)	(4.823)
Fexp	0.030***	0.024***
	(14.692)	(5.445)
Gexp	0.536***	
	(4.171)	
Portfolio size	0.116***	
	(3.344)	
Portfolio Gics	-1.383***	
	(-5.256)	
Relative EPS Optimism	6.658***	9.730***
	(5.159)	(3.151)
All-star	13.591***	
	(6.797)	
Drop Coverage	-15.674***	-12.440**
	(-9.927)	(-2.029)
Top 10	14.969***	-5.296
	(12.467)	(-0.472)
Investment Bank Affiliation	3.511	-4.938
	(1.507)	(-0.923)
Broker Ind Specialization	-0.001	-0.244***

	(-0.073)	(-3.422)
Industry-Year Fixed Effects	Y	N
Analyst-Year Fixed Effects	N	Y
R^2	10.73%	40.02%
N	110,551	35,206

Table 4. Characteristics of Top Pick Stocks

This table present logistic regression results for characteristics of top picks vs all buy recommendations issued between 1999 and 2016 i) in the same industry at the same year (i.e., industry-year matched) in Model 1, ii) by the same analyst at the same year (i.e., analyst-year matched) as in Models 2 and 3. The dependent variable equals one if a stock is designated as a top pick, and zero if a stock carries a buy recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations (Industry-year matched)	Top Picks vs Buy Recommendations (Analyst-year matched)	Top Picks vs Buy Recommendations (Analyst-year matched)
	Model 1	Model 2	Model 3
Size	0.486***	0.638***	0.730***
	(5.580)	(3.867)	(4.506)
BM	-60.050***	-72.820***	-71.310***
	(-8.615)	(-5.370)	(-5.419)
Institutional holding	205.840***	238.740***	250.300***
	(9.230)	(6.535)	(6.972)
Turnover	21.900***	24.210***	23.760***
	(4.406)	(2.687)	(2.709)
SSA coverage	0.745***	1.390***	1.370***
	(3.091)	(2.951)	(2.965)
Idiosyncratic volatility	-74.120***	-47.860***	-43.840***
	(-9.589)	(-3.280)	(-3.066)
Dispersion	-1044.690***	-2613.410***	-1890.440***
	(-5.162)	(-6.224)	(-5.021)
Past 12-m return	0.187***	0.345***	26.290***
	(4.663)	(4.380)	(3.515)
Investment Bank Affiliation	68.090***	55.850***	57.490***
	(6.129)	(3.293)	(3.463)
Relative EPS Optimism	11.260***	16.510***	12.990***
	(7.038)	(4.523)	(3.733)
% Target Price Implied Return	58.590***	175.220***	
	(7.771)	(10.743)	
Target Price Implied Return Rank #1			98.960***
			(5.890)
Target Price Implied Return Rank #2			92.140***
			(5.843)
Target Price Implied Return Rank #3			101.680***
			(7.206)
Target Price Implied Return Rank #4			75.440***
			(5.451)
Target Price Implied Return Rank #5			56.200***
			(4.111)

Industry-Year Fixed Effects	Y	N	N
Analyst-Year Fixed Effects	N	Y	Y
R^2	2.10%	32.46%	31.48%
N	140,162	7,499	7,499

Table 5. Investment Value of Top Picks: Calendar-time Portfolios

This table presents calendar-time monthly portfolio returns of the investment value of top picks vs all buy recommendations issued i) by the same analyst at the same year (i.e., analyst-year matched) in Panel A ii) in the same industry at the same year (i.e., industry-year matched) in Panel B, between 1999 and 2016. For the calendar-time portfolio of top picks, we skip a trading day between the announcement of top pick and inclusion into the portfolio to ensure the information is publicly available to all market participants. Top pick portfolios are then rebalanced on a daily basis when a new top pick is announced or current top pick designation expires, is reiterated, or removed before its expiration. For buy recommendation portfolios, we follow an analogous methodology with the exception of expiration dates. Monthly abnormal portfolio returns are reported using Daniel, Grinblatt, Titman and Wermers (1997) (DGTW) characteristic-adjusted returns and risk-adjustments using the Fama and French (1993) three-factor model (*3*-Factor alpha), with the addition of Carhart (1997)'s momentum factor (4-Factor alpha*)*, the Pastor and Stambaugh (2003) liquidity factor (5-Factor alpha*)*, the Fama-French short-term reversal factor (6-Factor alpha*)*, and the long-term reversal factor (7-Factor alpha*)*. Information on Top Picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Top picks vs Buy Recommendations (Analyst-Year Matched)

	Top Picks	Buy Recommendations	Difference
DGTW	1.331***	0.514***	0.816***
	(6.065)	(2.870)	(3.250)
3-Factor alpha	1.349***	0.400*	0.948***
	(5.402)	(1.900)	(3.770)
4-Factor alpha	1.413***	0.473**	0.939***
	(5.715)	(2.290)	(3.730)
5-Factor alpha	1.319***	0.395*	0.924***
	(5.299)	(1.900)	(3.640)
6-Factor alpha	1.328***	0.364*	0.964***
	(5.328)	(1.750)	(3.800)
7-Factor alpha	1.303***	0.347*	0.955***
	(5.300)	(1.680)	(3.770)

Panel B: Top picks vs Buy Recommendations (Industry-Year Matched)

	Top Picks	Buy Recommendations	Difference
DGTW	1.331***	0.432***	0.899***
	(6.065)	(4.290)	(4.170)
3-Factor alpha	1.349***	0.178	1.171***
	(5.402)	(1.360)	(5.290)
4-Factor alpha	1.413***	0.283**	1.130***
	(5.715)	(2.430)	(5.130)
5-Factor alpha	1.319***	0.216*	1.103***
	(5.299)	(1.840)	(4.970)
6-Factor alpha	1.328***	0.123	1.205***
	(5.328)	(1.080)	(5.470)
7-Factor alpha	1.303***	0.112	1.191***
	(5.300)	(1.000)	(5.430)

Table 6. Investment Value of Top Picks: Panel Regressions

This table presents panel regressions of the investment value of top picks vs all buy ecommendations issued i) by rthe same analyst at the same year (i.e., analyst-year matched) in Model 1 ii) in the same industry at the same year (i.e., industry-year matched) in Model 2 between 1999 and 2016. For top picks, we skip a trading day between the announcement of top pick and inclusion into the portfolio to ensure the information is publicly available to all market participants. Top pick portfolios are then rebalanced on a daily basis when a new top pick is announced or current top pick designation expires, is reiterated, or removed before its expiration. For buy recommendation portfolios, we follow an analogous methodology with the exception of expiration dates. The dependent variable is characteristic-adjusted stock returns (DGTW). Regressions are run daily but are converted into monthly coefficients for ease of interpretation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4
Top Pick	0.644***	0.838***	0.593***	0.803***
	(4.385)	(6.218)	(4.064)	(5.965)
Strong Buy		0.198***		0.068*
		(5.077)		(1.732)
Size	-0.135***	-0.125***	-0.093***	-0.088***
	(-4.429)	(-11.223)	(-3.080)	(-7.901)
BM	0.323***	0.364***	0.335***	0.353***
	(4.068)	(10.856)	(4.232)	(10.502)
Institutional holding	-0.507*	-0.207*	-0.165	-0.008
	(-1.725)	(-1.870)	(-0.565)	(-0.068)
Turnover	-0.113**	-0.262***	-0.194***	-0.309***
	(-2.126)	(-12.907)	(-3.652)	(-15.254)
Dispersion	0.037**	-0.022***	0.029*	-0.026***
	(2.456)	(-3.405)	(1.906)	(-4.059)
Past 12-month return	-0.970***	-0.456***	-0.758***	-0.391***
	(-14.210)	(-16.990)	(-11.152)	(-14.562)
SSA coverage	-0.002	-0.003**	0.002	-0.001
	(-0.454)	(-2.131)	(0.357)	(-0.622)
Fexp	0.009	0.017***	0.012	0.016***
	(0.888)	(3.982)	(1.262)	(3.718)
Gexp		-0.005*		-0.007**
		(-1.941)		(-2.432)
Portfolio size		0.002**		0.001
		(2.108)		(1.555)
Portfolio Gics		-0.005		-0.001
		(-0.934)		(-0.124)
Relative EPS Optimism	-0.373***	-0.397***	-0.301***	-0.325***
	(-5.092)	(-13.575)	(-4.126)	(-11.084)
All-star		0.081*		0.051

		(1.948)		(1.237)
Drop coverage	-0.801***	-0.454***	-0.710***	-0.361***
	(-5.490)	(-12.434)	(-4.864)	(-9.851)
Top 10	-0.524*	-0.004	-0.192	-0.036
	(-1.720)	(-0.172)	(-0.626)	(-1.423)
Investment Bank Affiliation	0.394*	-0.161	0.410*	-0.140
	(1.849)	(-1.631)	(1.933)	(-1.424)
Broker Ind Specialization	0.302*	0.146***	0.360**	0.157***
	(1.715)	(4.388)	(2.053)	(4.715)
Year-month Fixed Effects	Y	Y	Y	Y
Industry-Year Fixed Effects	N	Y	N	Y
Analyst-Year Fixed Effects	Y	N	Y	N
Industry Fixed Effects	Y	N	Y	N
R^2	0.21%	0.10%	0.20%	0.09%
N	5,677,086	24,621,739	5,536,592	23,991,011

Table 7. Characteristics of Good and Bad Top Pick Stocks

This table present logistic regression results for characteristics of Good (Bad) Top Picks vs all Buy Recommendations issued i) in the same industry at the same year (i.e., industry-year matched) in Model 1, ii) by the same analyst at the same year (i.e., analyst-year matched) in Model 2 between 1999 and 2016. The dependent variable equals one if a stock is designated as *Good (Bad) Top Pick*, and zero if a stock carries a buy recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively

Panel A: Good Top picks vs Buy Stock Recommendations

	Good Top Picks vs Buy Recommendations (*Industry-year matched*)	Good Top Picks vs Buy Recommendations (*Analyst-year matched*)
	Model 1	Model 2
Size	0.878**	1.260**
	(2.412)	(2.234)
BM	-92.460***	-66.690*
	(-2.611)	(-1.843)
Institutional holding	201.800**	441.010***
	(2.137)	(3.529)
Turnover	37.870*	61.070**
	(1.760)	(2.293)
SSA coverage	-0.697	-3.130**
	(-0.697)	(-2.204)
Idiosyncratic volatility	-92.840***	-53.180
	(-2.804)	(-1.200)
Dispersion	-187.370	-7048.920***
	(-0.493)	(-3.614)
Past 12-m return	-0.039	-0.051
	(-0.187)	(-0.179)
Relative EPS Optimism	12.020**	30.740**
	(2.143)	(2.400)
% Target Price Implied Return	80.260***	237.100***
	(2.903)	(4.465)
Investment Bank Affiliation	8.520	273.570
	(0.142)	(1.268)
Industry-Year Fixed Effects	Y	N
Analyst-Year Fixed Effects	N	Y
R^2	0.57%	28.05%
N	42,952	730

Panel B: Bad Top picks vs Buy Stock Recommendations

	Bad Top Picks vs Buy Recommendations (*Industry-year matched)*	Bad Top Picks vs Buy Recommendations (*Analyst-year matched)*
	Model 1	Model 2
Size	0.535	0.646
	(0.939)	(0.991)
BM	-56.240	60.440
	(-1.605)	(1.441)
Institutional holding	369.850***	150.110
	(2.999)	(1.096)
Turnover	-4.400	40.590
	(-0.174)	(1.537)
SSA coverage	-0.811	1.230
	(-0.601)	(0.597)
Idiosyncratic volatility	-57.990	-168.800***
	(-1.504)	(-3.162)
Dispersion	-210.160	-4199.320***
	(-0.374)	(-3.249)
Past 12-m return	0.362**	0.179
	(2.178)	(0.712)
Relative EPS Optimism	4.570	-7.160
	(0.609)	(-0.571)
% Target Price Implied Return	60.480	52.380
	(1.471)	(1.216)
Investment Bank Affiliation	103.520**	139.980**
	(2.187)	(2.139)
Industry-Year Fixed Effects	Y	N
Analyst-Year Fixed Effects	N	Y
R^2	0.53%	33.77%
N	41,426	620

Table 8. Top Picks and Market Reactions

This table presents panel regressions of cumulative CRSP VW-Index adjusted returns (i.e., CAR) over [0,+1] event window surrounding the announcement of a top pick relative to all buy recommendations i) issued in the same industry at the same year (i.e., industry-year matched) ii) issued in the same industry by the same analyst at the same year (i.e., analyst-year matched) between 1999 and 2014. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. All-star information is retrieved from *Institutional Investor Magazine*. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations (*Industry-year matched*)	Top Picks vs Buy Recommendations (*Analyst-year matched*)	Good Top Picks vs Buy Recommendations (*Industry-year matched*)	Good Top Picks vs Buy Recommendations (*Analyst-year matched*)	Bad Top Picks vs Buy Recommendations (*Industry-year matched*)	Bad Top Picks vs Buy Recommendations (*Analyst-year matched*)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	0.315***	0.218**				
	(3.836)	(2.043)				
Good Top Pick			0.945***	0.576**		
			(2.644)	(2.012)		
Bad Top Pick					-1.206**	-0.664***
					(-2.433)	(-2.669)
Strong Buy	0.463***		0.288***		0.333***	
	(17.553)		(6.820)		(7.461)	
Size	-0.002***	0.000	0.000	-0.004	-0.001	0.020***
	(-2.977)	(0.042)	(0.296)	(-0.946)	(-1.532)	(3.358)
BM	-0.073***	0.231	-0.097***	1.326***	-0.073***	-0.788***
	(-5.719)	(1.196)	(-3.909)	(2.729)	(-2.834)	(-2.585)
Institutional holding	0.953***	-0.120	0.742***	-0.698	0.740***	4.889**
	(8.984)	(-0.230)	(4.558)	(-0.411)	(4.255)	(2.163)
Turnover	-0.178***	-0.167	-0.129***	-0.713*	-0.050	-0.010
	(-6.794)	(-1.142)	(-2.914)	(-1.961)	(-1.080)	(-0.027)
SSA coverage	-0.018***	-0.010	-0.024***	-0.014	-0.020***	-0.035
	(-12.348)	(-1.495)	(-10.172)	(-0.807)	(-7.945)	(-1.184)
Dispersion	0.000	-1.881	0.000***	-25.336***	0.000***	47.549***
	(1.462)	(-0.528)	(7.556)	(-3.653)	(9.512)	(4.518)
Past 12-month return	0.664***	0.771***	0.746***	-0.097	0.902***	0.595

	(21.902)	(4.852)	(14.620)	(-0.231)	(14.529)	(1.075)
Idiosyncratic volatility	1.318***	1.511***	1.590***	1.881***	1.508***	1.340*
	(30.276)	(6.821)	(22.261)	(2.823)	(19.875)	(1.665)
Fexp	0.047***	0.018	0.057***	-0.126**	0.052***	0.125*
	(11.548)	(1.074)	(8.815)	(-2.157)	(7.511)	(1.739)
Gexp	0.013***		0.016***		0.018***	
	(4.482)		(3.820)		(4.016)	
Portfolio size	-0.020***		-0.034***		-0.030***	
	(-10.916)		(-10.539)		(-9.097)	
Portfolio Gics	-0.027***		-0.016		-0.008	
	(-3.296)		(-1.123)		(-0.572)	
Relative EPS Optimism	0.027***	-0.020	0.005	-0.146***	0.019*	0.632***
	(4.331)	(-0.504)	(0.459)	(-2.931)	(1.685)	(3.183)
All-star	0.196***		0.283***		0.186**	
	(4.563)		(3.629)		(2.193)	
Drop coverage	-0.215***	-0.423	-0.238***	2.250*	-0.175**	2.771***
	(-5.662)	(-1.406)	(-3.639)	(1.831)	(-2.560)	(2.775)
Top 10	0.322***	-0.090	0.311***	-0.551	0.339***	-6.565***
	(11.707)	(-0.123)	(6.995)	(-0.627)	(7.066)	(-2.800)
Investment Bank Affiliation	-0.043	0.057	-0.027	-7.326***	-0.021	-1.135
	(-0.409)	(0.170)	(-0.174)	(-4.308)	(-0.112)	(-1.204)
Broker Ind specialization	-0.075**	1.363***	-0.066	4.856***	-0.053	1.087**
	(-2.032)	(3.211)	(-1.089)	(5.439)	(-0.843)	(2.164)
Industry-Year Fixed Effects	Y	N	Y	N	Y	N
Analyst-Year Fixed Effects	N	Y	N	Y	N	Y
R^2	4.41%	33.28%	6.44%	35.24%	5.99%	36.48%
N	166,459	8,322	48,740	927	48,017	800

Table 9. Institutional Trading Behavior of Top Picks

This table presents panel regressions of the interactions between institutional trading imbalance over [0, +1] surrounding the announcement of a top pick relative to all buy recommendations i) issued in the same industry at the same year (i.e. industry-year matched) ii) issued in the same industry by the same analyst at the same year (i.e., analyst-year matched) between 1999 and 2014. The dependent variable equals the total institutional trading imbalance over [0,+1] surrounding the announcement of a top pick or a stock recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Information on daily institutional trading is from *Ancerno Ltd* from 1999 to 2014. All-star information is retrieved from *Institutional Investor Magazine*. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations (*Industry-year matched)*	Top Picks vs Buy Recommendations (*Analyst-year matched)*	Good Top Picks vs Buy Recommendations (*Industry-year matched)*	Good Top Picks vs Buy Recommendations (*Analyst-year matched)*	Bad Top Picks vs Buy Recommendations (*Industry-year matched)*	Bad Top Picks vs Buy Recommendations (*Analyst-year matched)*
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	1.128***	1.271***				
	(3.162)	(2.632)				
Good Top Pick			2.991**	5.043***		
			(2.091)	(2.968)		
Bad Top Pick					-4.709***	-3.582*
					(-3.317)	(-1.784)
Strong Buy	0.084		0.028		0.296*	
	(0.743)		(0.174)		(1.688)	
Size	-0.001	0.013	-0.004	-0.020	-0.013***	-0.065
	(-0.588)	(1.566)	(-1.538)	(-0.593)	(-4.483)	(-0.681)
BM	0.007	0.672	-0.658***	-1.238	-0.070	-3.923
	(0.050)	(0.976)	(-3.081)	(-0.519)	(-0.323)	(-1.000)
Institutional holding	-0.524	-1.817	-1.419**	4.449	2.982***	1.996
	(-1.112)	(-0.763)	(-2.074)	(0.418)	(4.030)	(0.193)
Turnover	0.688***	1.622***	-0.336**	-1.728	1.396***	0.767
	(6.412)	(2.700)	(-2.127)	(-0.582)	(8.523)	(0.585)
SSA coverage	0.000	0.020	0.043***	-0.041	-0.004	0.348**
	(0.000)	(0.654)	(4.943)	(-0.362)	(-0.396)	(1.989)
Dispersion	0.532	3.232	1.050	-52.104	-0.417	193.569***
	(1.279)	(0.370)	(1.119)	(-0.702)	(-0.774)	(3.409)
Past 12-month return	0.841***	0.162	0.922***	1.677	0.693***	-1.251

	(7.744)	(0.268)	(5.960)	(0.451)	(3.760)	(-0.597)
Idiosyncratic volatility	0.318*	0.947	0.653**	-3.707	1.282***	-5.141
	(1.860)	(1.009)	(2.524)	(-0.978)	(4.785)	(-1.559)
Fexp	-0.021	-0.091	-0.054**	-0.532*	0.059**	-0.590*
	(-1.180)	(-1.243)	(-2.126)	(-1.836)	(2.000)	(-1.922)
Gexp	-0.008		0.001		-0.002	
	(-0.714)		(0.063)		(-0.111)	
Portfolio size	0.001		-0.013*		-0.011	
	(0.769)		(-1.711)		(-1.264)	
Portfolio Gics	-0.008		0.035		-0.004	
	(-0.394)		(0.962)		(-0.098)	
Relative EPS Optimism	-0.301**	0.344	-0.364*	3.878*	-0.116	-2.669
	(-2.339)	(0.509)	(-1.828)	(1.866)	(-0.550)	(-0.623)
All-star	0.344*		0.442		0.688*	
	(1.744)		(1.394)		(1.956)	
Drop coverage	0.083	0.637	-0.233	-11.245	-0.137	-6.641
	(0.516)	(0.424)	(-0.934)	(-1.288)	(-0.537)	(-1.039)
Top 10	0.211*	1.420	0.185	-0.726	-0.130	-7.413
	(1.846)	(0.763)	(1.107)	(-0.090)	(-0.720)	(-1.338)
Investment Bank Affiliation	0.080	-0.507	0.403	17.764	0.247	2.525
	(0.256)	(-0.499)	(0.831)	(1.334)	(0.348)	(0.490)
Broker Ind specialization	0.324**	4.155**	0.685***	23.986***	0.367	0.535
	(2.112)	(2.304)	(3.061)	(3.342)	(1.624)	(0.230)
Industry-Year Fixed Effects	Y	N	Y	N	Y	N
Analyst-Year Fixed Effects	N	Y	N	Y	N	Y
R^2	0.67%	26.23%	0.79%	32.57%	2.51%	47.20%
N	117,518	6,976	38,226	272	29,475	219

Table 10. Retail Investors' Trading Behavior of Top Picks

This table presents panel regressions of the interactions between retail trading imbalance over [0,+1] surrounding the announcement of a top pick relative to all Buy Recommendations i) issued in the same industry at the same year (i.e., industry-year matched) ii) issued in the same industry by the same analyst at the same year (i.e., analyst-year matched) between 1999 and 2016. The dependent variable is the total retail trading imbalance over [0,+1] surrounding the announcement of a top pick or a stock recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information are obtained from CRSP/Compustat. Information on daily retail trading is from *TAQ* from 1999 to 2016. All-star information is retrieved from *Institutional Investor Magazine*. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations (*Industry-year matched*)	Top Picks vs Buy Recommendations (*Analyst-year matched*)	Good Top Picks vs Buy Recommendations (*Industry-year matched*)	Good Top Picks vs Buy Recommendations (*Analyst-year matched*)	Bad Top Picks vs Buy Recommendations (*Industry-year matched*)	Bad Top Picks vs Buy Recommendations (*Analyst-year matched*)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	0.446*	1.573***				
	(1.909)	(6.463)				
Good Top Pick			-1.516**	-1.840**		
			(-2.337)	(-2.046)		
Bad Top Pick					0.299	-1.706
					(0.281)	(-1.067)
Strong Buy	-0.119*		-0.095		-0.070	
	(-1.814)		(-1.010)		(-0.660)	
Size	0.009***	0.011***	0.008***	0.023	0.010***	0.019
	(7.500)	(2.750)	(5.333)	(1.065)	(4.545)	(0.518)
BM	0.057	0.186	0.159	3.090	0.197	0.618
	(0.576)	(0.453)	(1.105)	(1.476)	(1.176)	(0.263)
Institutional holding	-2.828***	0.142	-2.459***	3.167	-2.319***	2.475
	(-9.395)	(0.160)	(-5.880)	(0.782)	(-5.324)	(0.603)
Turnover	0.928***	0.085	0.985***	2.134	1.019***	0.583
	(11.235)	(0.279)	(9.020)	(0.972)	(7.998)	(0.618)
SSA coverage	-0.014***	-0.024*	-0.012**	-0.020	-0.012**	-0.128
	(-3.684)	(-1.875)	(-2.308)	(-0.333)	(-2.264)	(-1.275)
Dispersion	0.837	2.801	2.718	-25.541*	0.006	78.596***
	(1.198)	(0.488)	(1.544)	(-1.693)	(0.013)	(3.228)

Past 12-month return	0.109	-0.199	0.107	0.397	0.206	-0.388
	(1.457)	(-0.695)	(0.944)	(0.289)	(1.638)	(-0.575)
Idiosyncratic volatility	0.992***	0.781*	1.103***	1.761	1.190***	-2.438
	(9.254)	(1.768)	(7.130)	(0.919)	(7.447)	(-1.397)
Fexp	-0.007	-0.078**	-0.021	0.210	-0.032*	-0.472**
	(-0.700)	(-2.484)	(-1.500)	(0.851)	(-1.963)	(-2.538)
Gexp	-0.002		0.001		0.000	
	(-0.299)		(0.111)		(0.000)	
Portfolio size	-0.001		-0.001		0.000	
	(-0.417)		(-0.222)		(0.000)	
Portfolio Gics	0.011		0.012		0.013	
	(0.753)		(0.571)		(0.542)	
Relative EPS Optimism	-0.002	0.061	0.111	-0.678	-0.010	0.270
	(-0.027)	(0.210)	(0.986)	(-0.754)	(-0.083)	(0.178)
All-star	0.232**		0.051		-0.016	
	(2.107)		(0.304)		(-0.088)	
Drop coverage	0.088	-0.875	0.050	-5.462**	0.145	-0.400
	(0.954)	(-1.318)	(0.411)	(-2.109)	(1.008)	(-0.240)
Top 10	0.158**	0.948	0.196**	2.073	0.182*	-5.330
	(2.300)	(0.837)	(2.021)	(1.365)	(1.676)	(-1.509)
Investment Bank Affiliation	0.107	-1.099*	0.443	-7.544***	0.026	0.522
	(0.393)	(-1.735)	(1.191)	(-2.776)	(0.068)	(0.244)
Broker Ind specialization	-0.085	0.745	-0.041	0.490	-0.170	0.602
	(-0.944)	(0.806)	(-0.313)	(0.321)	(-1.221)	(0.293)
Industry-Year Fixed Effects	Y	N	Y	N	Y	N
Analyst-Year Fixed Effects	N	Y	N	Y	N	Y
R^2	1.69%	39.70%	2.07%	32.29%	2.03%	31.29%
N	65,254	4,529	30,928	219	27,053	223

Table 11. Career Consequences of Top Picks: Demotion vs Promotions

This table presents logistic regression results on the career consequences of top picks for sell-side analysts. The dependent variable equals one if analyst *i* experiences demotion or promotion at year *t*+1, and zero otherwise. An analyst movement is defined as a demotion (promotion) if an analyst *i* moves from a top 10 (non-top 10) decile broker to a non-top 10 (top 10) decile broker. Analyst *i* is classified as a "*Good (Bad) Top Picker*" at year *t* if abnormal stock outperformance of her top pick selection (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the highest (lowest) quartile compared to that of top picks of all analysts at year *t* for the same industry *j*. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and time level. Year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Panel A. Demotion				Panel B. Promotion			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Top Pick Analyst	23.590		-5.930		-18.030		-21.590	
	(1.286)		(-0.251)		(-0.540)		(-0.539)	
Bad Top Picker Analyst		111.640***		218.310***		-53.750		6.620
		(3.864)		(3.311)		(-0.740)		(0.069)
Good Top Picker Analyst		-90.310		-155.880**		-10.410		-1.330
		(-1.521)		(-2.358)		(-0.143)		(-0.015)
Average Size in Portfolio	-2.020	-1.930	-14.530**	-14.100**	-9.800**	-9.780**	-3.630	-3.570
	(-0.415)	(-0.395)	(-2.218)	(-2.143)	(-2.192)	(-2.188)	(-0.599)	(-0.589)
Average BM in Portfolio	-44.150***	-44.250***	1.970	1.930	-50.040***	-49.960***	-8.330	-8.190
	(-5.966)	(-5.972)	(0.192)	(0.187)	(-5.445)	(-5.436)	(-0.713)	(-0.702)
Average Fexp	4.410	4.660	4.370	4.550	-4.600	-4.690	-6.620	-6.760
	(1.202)	(1.266)	(0.871)	(0.897)	(-1.165)	(-1.187)	(-1.329)	(-1.360)
Gexp	3.080**	2.960**	3.480*	3.460*	-0.886	-0.870	-3.420*	-3.370*
	(2.139)	(2.056)	(1.758)	(1.730)	(-0.642)	(-0.630)	(-1.954)	(-1.937)
Portfolio size	-0.555	-0.545	-1.320	-1.550	2.160***	2.150***	1.860*	1.810*
	(-0.803)	(-0.793)	(-1.375)	(-1.610)	(2.983)	(2.974)	(1.824)	(1.775)
Portfolio Gics	-6.250*	-6.130*	-0.855	-0.360	-15.550***	-15.520***	-6.900*	-6.780*
	(-1.894)	(-1.858)	(-0.200)	(-0.083)	(-4.829)	(-4.820)	(-1.721)	(-1.691)
Broker Ind Specialization	30.320	30.130	42.840	43.740	2.390	2.470	22.310	22.920
	(1.475)	(1.463)	(1.504)	(1.528)	(0.166)	(0.172)	(1.224)	(1.258)
All-star	-79.200***	-78.050***	-85.030***	-83.230***	51.650	51.660	109.850**	108.250**

	(-4.922)	(-4.851)	(-4.403)	(-4.270)	(1.442)	(1.442)	(2.270)	(2.241)
Average Buy Rec return	-40.550	-41.459*	-54.736	-54.433	-13.572	-13.514	-13.611	-13.716
	(-1.638)	(-1.679)	(-1.434)	(-1.421)	(-0.500)	(-0.498)	(-0.358)	(-0.361)
Investment Bank Affiliation	-219.870***	-223.590***	-132.860	-163.010*	55.970	56.860	365.400***	370.030***
	(-2.837)	(-2.874)	(-1.600)	(-1.852)	(0.795)	(0.808)	(2.772)	(2.806)
Average Relative EPS Optimism	67.590**	68.770**	88.080*	91.660**	-26.590	-27.160	-94.830**	-95.190**
	(2.088)	(2.126)	(1.936)	(2.004)	(-0.777)	(-0.794)	(-2.184)	(-2.192)
Average Report count	5.600**	5.390**	6.770*	5.790	9.160***	9.180***	8.980**	8.950**
	(2.121)	(2.042)	(1.870)	(1.586)	(3.148)	(3.155)	(2.326)	(2.319)
Average Drop Coverage	303.440***	302.660***	170.540***	170.600***	77.190***	77.450***	-149.280***	-149.330***
	(13.256)	(13.222)	(5.188)	(5.163)	(2.727)	(2.736)	(-4.189)	(-4.190)
Average PMAFE	21.100***	21.190***	24.830**	25.480**	6.440	6.410	-14.000	-13.920
	(3.231)	(3.245)	(2.099)	(2.141)	(0.756)	(0.752)	(-1.143)	(-1.136)
Average Institutional holding	-51.820	-51.020	17.120	22.230	92.230**	92.390**	43.470	42.610
	(-1.235)	(-1.218)	(0.294)	(0.380)	(2.125)	(2.129)	(0.759)	(0.744)
Average Turnover	34.670***	34.420***	3.680	3.070	30.370***	30.330***	8.180	8.340
	(3.781)	(3.754)	(0.303)	(0.252)	(3.227)	(3.223)	(0.691)	(0.704)
Average Dispersion	-75.070	-79.730	-138.220	-203.220	-780.910**	-775.900**	-1122.150***	-1130.640***
	(-0.229)	(-0.243)	(-0.313)	(-0.457)	(-2.292)	(-2.280)	(-2.588)	(-2.607)
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	2.17%	2.24%	10.96%	12.17%	1.52%	1.52%	9.82%	9.80%
N	17,407	17,407	1,516	1,516	13,436	13,436	1,664	1,664

Table 12. Career Consequences of Top Picks: Selection into Institutional Investors' All-Star team

This table presents logistic regression results on the career consequences of top picks for sell-side analysts. The dependent variable equals one if analyst *i* was voted an all-star in the October issue of *Institutional Investor Magazine* in year *t*, and zero otherwise. Analyst *i* is classified as a "*Good (Bad) Top Picker*" at year *t* if abnormal stock outperformance of her top pick selection (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the highest (lowest) quartile compared to that of top picks of all analysts at year *t* for the same industry *j*. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and time level. Year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4
Top Pick Analyst	60.670***		101.350***	
	(4.736)		(5.306)	
Bad Top Picker Analyst		-14.750		-92.140
		(-0.386)		(-0.896)
Good Top Pick Analyst		72.770***		89.050**
		(2.646)		(2.298)
Average Size in Portfolio	50.430***	50.260***	55.670***	55.240***
	(17.820)	(17.823)	(12.947)	(12.907)
Average BM in Portfolio	-16.070***	-16.640***	-15.720**	-16.200**
	(-3.176)	(-3.289)	(-2.008)	(-2.080)
Average Fexp	6.030***	6.160***	-14.470***	-14.160***
	(3.486)	(3.561)	(-4.019)	(-3.955)
Gexp	3.990***	3.990***	0.540	0.576
	(5.089)	(5.096)	(0.394)	(0.420)
Portfolio size	6.220***	6.280***	7.250***	7.350***
	(19.021)	(19.205)	(14.414)	(14.671)
Portfolio Gics	-10.120***	-10.410***	-23.260***	-23.610***
	(-3.614)	(-3.718)	(-4.624)	(-4.703)
Broker Ind Specialization	-126.740***	-127.040***	-157.980***	-160.360***
	(-10.131)	(-10.163)	(-7.459)	(-7.546)
All-star (t-1)	534.620***	535.620***		
	(43.571)	(43.688)		
Average Buy Rec return	46.257**	45.245**	2617.270	2554.560
	(2.207)	(2.161)	(0.826)	(0.811)
Investment Bank Affiliation	187.890***	190.780***	1.553***	1.624***
	(7.101)	(7.221)	(4.055)	(4.268)
Average Relative EPS Optimism	-48.980***	-51.710***	-17.510	-19.130
	(-2.638)	(-2.785)	(-0.630)	(-0.689)
Average Report count	7.990***	8.310***	9.990***	10.330***
	(6.242)	(6.543)	(5.911)	(6.186)
Average Drop Coverage	-241.910***	-241.980***	-216.690***	-214.910***
	(-13.583)	(-13.579)	(-6.912)	(-6.875)
Average PMAFE	-21.390***	-21.680***	-28.180***	-27.710***

	(-3.332)	(-3.372)	(-2.636)	(-2.614)
Average Institutional holding	-5.060	-2.490	57.010	59.850
	(-0.173)	(-0.085)	(1.251)	(1.315)
Average Turnover	-8.070	-8.870	-11.100	-11.800
	(-1.349)	(-1.486)	(-1.213)	(-1.295)
Average Dispersion	410.800**	400.070**	566.880**	554.380**
	(2.242)	(2.180)	(2.054)	(2.009)
Year Fixed Effects	Y	Y	Y	Y
R^2	20.94%	20.91%	3.60%	3.54%
N	34,520	34,520	30,627	30,627

Table 13. Reputational Consequences of Top Picks with Financial Markets

This table presents panel regression results on the reputational consequences of top picks with financial markets. The dependent variable is DGTW-adjusted stock market reactions over [0, +2] event window surrounding the announcement of upgrades or downgrades by the same analyst for *non-top pick* stocks. Analyst *i* is classified as a "*Good (Bad) Top Picker*" at year *t* if abnormal stock outperformance of her top pick selection (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the highest (lowest) quartile compared to that of top picks of all analysts at year *t* for the same industry *j*. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Upgrades (Non-top pick Firms)				Downgrades (Non-top pick Firms)			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Top Pick Analyst	-0.005				-0.008			
	(-0.029)				(-0.036)			
Bad Top Picker		-0.731**		-0.721**		0.924**		0.903**
		(-2.104)		(-2.073)		(2.293)		(2.238)
Good Top Picker			0.198	0.164			-0.475	-0.436
			(0.645)	(0.534)			(-1.253)	(-1.149)
Revision	0.517***	0.517***	0.517***	0.517***	0.786***	0.785***	0.786***	0.785***
	(8.560)	(8.562)	(8.555)	(8.558)	(10.982)	(10.969)	(10.981)	(10.968)
Size	-0.482***	-0.482***	-0.482***	-0.482***	0.764***	0.764***	0.764***	0.764***
	(-17.934)	(-17.920)	(-17.936)	(-17.921)	(23.809)	(23.813)	(23.813)	(23.816)
BM	-0.088**	-0.089**	-0.089**	-0.089**	0.166***	0.166***	0.166***	0.166***
	(-2.279)	(-2.289)	(-2.281)	(-2.291)	(3.609)	(3.612)	(3.615)	(3.618)
Institutional holding	-0.160	-0.160	-0.160	-0.160	1.035***	1.037***	1.036***	1.038***
	(-1.247)	(-1.248)	(-1.251)	(-1.251)	(6.848)	(6.863)	(6.856)	(6.870)
Turnover	0.153***	0.154***	0.153***	0.153***	-0.628***	-0.629***	-0.628***	-0.629***
	(3.744)	(3.748)	(3.740)	(3.746)	(-13.000)	(-13.024)	(-13.002)	(-13.024)
Earnings Forecast Dispersion	4.136***	4.152***	4.137***	4.153***	-5.671***	-5.669***	-5.669***	-5.666***
	(4.639)	(4.657)	(4.640)	(4.657)	(-5.630)	(-5.628)	(-5.628)	(-5.625)
Past 12-month return	-0.402***	-0.402***	-0.402***	-0.402***	0.267***	0.268***	0.267***	0.268***
	(-6.454)	(-6.457)	(-6.453)	(-6.457)	(3.722)	(3.732)	(3.724)	(3.733)

SSA coverage	-0.024***	-0.024***	-0.024***	-0.024***	0.004	0.004	0.004	0.004
	(-6.408)	(-6.422)	(-6.405)	(-6.419)	(0.970)	(0.971)	(0.967)	(0.968)
Fexp	0.011	0.011	0.011	0.011	-0.001	-0.001	-0.001	-0.001
	(1.148)	(1.156)	(1.137)	(1.147)	(-0.110)	(-0.111)	(-0.093)	(-0.095)
Gexp	0.011	0.011	0.010	0.010	-0.266*	-0.261*	-0.264*	-0.259*
	(0.110)	(0.107)	(0.102)	(0.101)	(-1.932)	(-1.894)	(-1.921)	(-1.886)
Portfolio size	0.004	0.004	0.004	0.004	-0.002	-0.002	-0.002	-0.002
	(1.531)	(1.530)	(1.529)	(1.528)	(-0.776)	(-0.779)	(-0.774)	(-0.777)
Portfolio Gics	0.019	0.019	0.019	0.019	-0.033	-0.033	-0.033	-0.033
	(0.715)	(0.710)	(0.722)	(0.715)	(-1.038)	(-1.040)	(-1.051)	(-1.052)
Relative EPS Optimism	-0.001	0.000	-0.001	0.000	0.245***	0.245***	0.246***	0.245***
	(-0.014)	(-0.008)	(-0.012)	(-0.006)	(4.130)	(4.122)	(4.138)	(4.130)
All-star	0.317**	0.317**	0.317**	0.316**	-0.385**	-0.382**	-0.382**	-0.379**
	(2.329)	(2.324)	(2.324)	(2.320)	(-2.325)	(-2.308)	(-2.308)	(-2.292)
Drop Coverage	-0.182**	-0.182**	-0.181**	-0.182**	0.166*	0.165*	0.165*	0.165*
	(-2.341)	(-2.347)	(-2.337)	(-2.344)	(1.909)	(1.904)	(1.909)	(1.903)
Top 10	0.254***	0.256***	0.253***	0.255***	-0.086	-0.088	-0.085	-0.087
	(2.809)	(2.827)	(2.800)	(2.819)	(-0.780)	(-0.796)	(-0.772)	(-0.788)
Investment Bank Affiliation	-0.016	-0.012	-0.016	-0.012	-0.609**	-0.608**	-0.608**	-0.607**
	(-0.074)	(-0.054)	(-0.073)	(-0.054)	(-2.328)	(-2.324)	(-2.322)	(-2.318)
Broker Ind Specialization	-0.060	-0.061	-0.060	-0.061	0.028	0.028	0.026	0.027
	(-0.730)	(-0.743)	(-0.727)	(-0.740)	(0.277)	(0.284)	(0.264)	(0.272)
Year-month Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Analyst Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	26.88%	26.89%	26.88%	26.89%	33.18%	33.19%	33.18%	33.54%
N	46,552	46,552	46,552	46,552	46,914	46,914	46,914	46,914

Online Appendix

Table A1. Investment Value of Buy Recommendations: Top Pick Analysts vs Other Analysts

This table presents calendar time monthly portfolio returns of the investment value of Buy Recommendations issued by top pick analysts to non-top pick analysts' Buy Recommendations in the same industry at the same year (i.e., industry-year matched) between 1999 and 2016. For the calendar-time portfolio of top picks, we skip a trading day between the announcement of top pick and inclusion into the portfolio. Portfolios are then rebalanced on a daily basis when a new buy recommendation is announced, reiterated, or removed. Monthly abnormal portfolio returns are reported using Daniel, Grinblatt, Titman and Wermers (1997) (DGTW) characteristic-adjusted returns and risk-adjustments using the Fama and French (1993) three-factor model (*3*-Factor alpha), with the addition of Carhart (1997)'s momentum factor (4-Factor alpha), the Pastor and Stambaugh (2003) liquidity factor (5-Factor alpha), the Fama-French short-term reversal factor (6-Factor alpha), and the long-term reversal factor (7-Factor alpha). Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Pick Analysts	Other Analysts	Difference
DGTW	0.514***	0.432***	0.081
	(2.870)	(4.290)	(0.500)
3-Factor alpha	0.400*	0.178	0.223
	(1.900)	(1.360)	(1.310)
4-Factor alpha	0.473**	0.283**	0.191
	(2.290)	(2.430)	(1.130)
5-Factor alpha	0.395*	0.216*	0.179
	(1.900)	(1.840)	(1.050)
6-Factor alpha	0.364*	0.123	0.241
	(1.750)	(1.080)	(1.420)
7-Factor alpha	0.347*	0.112	0.236
	(1.680)	(1.000)	(1.390)

Table A2. Investment Value of Top Picks: Calendar-time Portfolios (Exclude +1, +5)

This table presents calendar time monthly portfolio returns of the investment value of Top Picks vs all Buy Recommendations issued i) by the same analyst at the same year (i.e., analyst-year matched) in Panel A ii) in the same industry at the same year (i.e., industry-year matched) in Panel B, between 1999 and 2016. For the calendar-time portfolio of top picks, we skip 5 trading days between the announcement of top pick and inclusion into the portfolio (*t+6*). Top pick portfolios are then rebalanced on a daily basis when a new top pick is announced or current top pick designation expires, is reiterated, or removed before its expiration. For buy recommendation portfolios, we follow an analogous methodology with the exception of expiration dates. Monthly abnormal portfolio returns are reported using Daniel, Grinblatt, Titman and Wermers (1997) (DGTW) characteristic-adjusted returns and risk-adjustments using the Fama and French (1993) three-factor model (*3*-Factor alpha), with the addition of Carhart (1997)'s momentum factor (4-Factor alpha), the Pastor and Stambaugh (2003) liquidity factor (5-Factor alpha), the Fama-French short-term reversal factor (6-Factor alpha), and the long-term reversal factor (7-Factor alpha). Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon.* Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Top picks vs Buy Recommendations (Analyst-Year Matched): (Exclude +1, +5)

	Top Pick	Buy Recommendation	Difference
DGTW	1.058***	0.384**	0.673***
	(4.761)	(0.030)	(2.630)
3-Factor alpha	1.092***	0.323	0.767***
	(4.333)	(1.486)	(2.980)
4-Factor alpha	1.152***	0.382*	0.768***
	(4.612)	(1.778)	(2.980)
5-Factor alpha	1.055***	0.302	0.753***
	(4.196)	(1.395)	(2.900)
6-Factor alpha	1.066***	0.266	0.800***
	(4.236)	(1.229)	(3.080)
7-Factor alpha	1.040***	0.242	0.796***
	(4.185)	(1.131)	(3.070)

Panel B: Top picks vs Buy Recommendations (Industry-Year Matched): (Exclude +1, +5)

	Top Pick	Buy Recommendations	Difference
DGTW	1.058***	0.225**	0.823***
	(4.761)	(2.120)	(3.770)
3-Factor alpha	1.092***	-0.026	1.103***
	(4.333)	(-0.190)	(4.920)
4-Factor alpha	1.152***	0.082	1.059***
	(4.612)	(0.680)	(4.760)
5-Factor alpha	1.055***	0.007	1.032***
	(4.196)	(0.050)	(4.600)
6-Factor alpha	1.066***	-0.088	1.136***
	(4.236)	(-0.740)	(5.100)
7-Factor alpha	1.040***	-0.098	1.122***
	(4.185)	(-0.830)	(5.060)