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Do Bold Prophecies Lead to Higher Profits?

A Study on the Profitability of Trading S&P 100 Companies Based on Analyst Consensus Recommendations, between 1994 and 2015, and the Impact of Regulation Fair Disclosure

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Abstract:

We find that non-herding ("bold") recommendations – defined as those deviating from last day's consensus by more than one level – had a greater investment value than herding recommendations prior to Regulation Fair Disclosure, which became effective in October, 2000. Indeed, a value-weighted portfolio that purchased S&P 100 companies with the most favourable consensus, made up of bold (all) recommendations, yielded a statistically significant (insignificant) annual abnormal gross return of 7.8% (3.8%), when rebalanced daily, over the period May 1994-Oct 2000. Unlike previous studies, we also find an economically, although not statistically, significant positive alpha net of transaction costs of 4.5% for the bold consensus. Surprisingly, the less sophisticated approach of restricting the consensus to upgrades and downgrades yielded not too distant results, with a statistically significant (insignificant) gross (net) alpha of 5.5% (1.8%). Our results raise the question whether the market was imperfect in the pre-regulation period, because investors could seemingly be rewarded for filtering public information, i.e. recommendations. All results remain robust to tests of investment delays, lower rebalancing frequencies, and business cycles.

Keywords: Stock recommendations, Sell-side analysts, Herding, Regulation Fair Disclosure

JEL Classification: G11, G24, G28

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1. Introduction

Brokerage houses spend over a billion dollars on sell-side research every year (Zacks Investment Research (2016)), presumably with the aim of delivering beneficial trading information to their clients. Stock recommendations are the most straightforward output from this research, as they represent "[…] a clear and unequivocal course of action rather than producing an estimate of a number, the interpretation of which is up to the user." (Elton et al. (1986)).

Both academics and practitioners have evaluated the investment value of recommendations over the years, despite academic theory claiming that one cannot profit from publicly available information, namely the semi-efficient market hypothesis. One such study – Barber et al. (2001) – sought to test the profitability of portfolios based on consensus, i.e. average, recommendations and found gross abnormal returns of more than four percent by "[…] purchasing (selling short) stocks with the most (least) favourable consensus recommendations, in conjunction with daily portfolio rebalancing and a timely response to recommendation changes".

In light of Barber et al.'s findings, one might question whether a more informative consensus can be found than the one based on all available recommendations. To answer this question, we turn to research within the field of analyst herding behavior, defined by Trueman (1994) as "[…] a tendency to report forecasts similar to those previously released by other analysts […]". Trueman argues that a consensus of all available recommendations is inappropriate as analysts tend to herd. Furthermore, Clement and Tse (2005) find that boldness may be a sign of private information, as it is positively associated with earnings-per-share forecast accuracy. Indeed, subsequent studies by Bagnoli et al. (2010) and Jegadeesh and Kim (2010), using different definitions of bold recommendations, find that such recommendations are generally more profitable and have a greater stock market impact.

The above motivates further investigation as to whether a trading strategy based on a consensus restricted to bold recommendations is more profitable than one based on all recommendations. To the best of our knowledge, the existing literature has yet to test for abnormal returns using bold consensus recommendations; it has either focused on average price reactions to recommendations (e.g. Stickel (1995) and Womack (1996)) or attempted to restrict the consensus to recommendations issued by analysts' with higher prior earnings forecast accuracy (Loh and Mian (2006)). Thus, the primary purpose of our thesis is to fill that gap.

We also look at the effects of Regulation Fair Disclosure, which addressed the issue of corporate managers handing private information to select analysts. The regulation was seemingly effective at reducing both conflicts of interest and access to such information (e.g. Gintschel and Markov (2004) and Mohanram and Sunder (2006)). Hence, we believe that boldness will not reflect private information to the same degree in the period following its implementation, which would then imply a reduction in investment value.

To test our hypotheses, we follow the trading strategy proposed by Barber et al. (2001) of forming portfolios based on consensus recommendations. We apply the strategy to recommendation data from I/B/E/S over the period May 1994-Dec 2015. Whereas Barber et al. use a large sample covering more than 3,500 companies per year on average, we focus only on S&P 100 companies. Our smaller sample makes the strategy more relevant for practitioners, as it requires less information processing of recommendations and avoids trading in less liquid stocks.

We further develop the trading strategy by applying it to bold recommendations only, using two definitions. The simpler version defines bold recommendations as those deviating from last day's consensus by at least one level (Bagnoli et al. (2010)), whereas the more complex one captures recommendations that are more bold, relative to the consensus, than the analyst's most recent recommendation for the same company (Jegadeesh and Kim (2010)). As much previous research has focused on upgrades and downgrades, also known as recommendation changes, we repeat the strategy using these recommendations only, for comparison. Finally, we divide our sample into two periods – before and after Regulation Fair Disclosure, corresponding to May 1994-Oct 2000 and Nov 2000-Dec 2015, respectively.

Contrary to what we expected, we cannot reliably re-affirm Barber et al.'s findings. While we find an economically significant gross annual alpha in the pre-regulation period of 3.8%, the alpha is not statistically significant at any reasonable level. However, the lack of support for Barber et al.'s results may simply reflect the characteristics of our sample. Indeed, Stickel (1995) found that large companies have smaller stock reactions to recommendation changes.

We find that prior to Regulation Fair Disclosure, a more profitable consensus could be found by restricting it to bold recommendations, defined as those recommendations that deviate at least one level from last day's consensus (Bagnoli et al.). To wit, we find that a portfolio of stocks with the most favourable bold (ordinary) consensus yielded statistically significant (insignificant) alphas of 7.8% (3.8%) in May 1994-Oct 2000. Surprisingly, the seemingly less sophisticated approach of restricting the consensus to recommendation changes also yielded not too distant results, with a statistically significant gross alpha of 5.5%. Unlike previous studies, we also find an economically, although not statistically, significant positive alpha net of transaction costs of 4.5% (1.8%) for the bold (changes) consensus portfolio.

In line with prior studies confirming Regulation Fair Disclosure's effectiveness (e.g. Kadan et al. (2009)), we do not find significant results for bold recommendations in the subsequent period, Nov 2000-Dec 2015.

We conclude that investors could, indeed, find a more profitable strategy by looking at bold recommendations prior to Regulation Fair Disclosure. The reduced access to private information has, however, led to a decrease in investment value of such recommendations. While we cannot re-affirm Barber et al.'s particular findings, our results nevertheless support their more general conclusion that investors may profit from publicly available information.

Our findings are robust to the effect of investment delays and business cycles. Moreover, testing for less frequent rebalancing yields even higher net alphas when looking at the bold consensus. Notably, these alphas prove to be statistically significant at the 10% level, indicating the potential for a more optimal rebalancing strategy than daily.

The remainder of this paper will be structured as follows: Section 2 features details about prior literature and our hypotheses. Section 3 presents our dataset and its sources. Section 4 explains how we construct our variables and regressions. Section 5 presents our results, both descriptive statistics and regressions. In Section 6, we conclude by discussing the implications of our findings and provide suggestions for future research. Robustness tests and additional tables are found in the Appendix.

2. Prior literature

2.1 The investment value of stock recommendations

Cowles (1933) was one of the first to evaluate the investment value of stock recommendations. Looking at stock recommendations issued by “16 leading financial services [firms]” over a four and a half year-long period, he found that the recommendations performed worse on average than the market in general. Furthermore, Cowles argued that even the best forecasters in his sample “probably were the results of chance”.

Cowles’s research was followed by a time gap, during which “[…] the research on analysts' recommendations in academic outlets was essentially non-existent until the 1960s and 1970s” (Michaely and Womack (2005)). Following this gap, several studies have supported Cowles’s findings, such as: Diefenbach (1972), Logue and Tuttle (1973), and Bidwell (1977).

More recent studies have contradicted Cowles’s findings, however. For example, Groth et al. (1979) examined one particular brokerage house’s recommendations over a seven year-long period and found its recommendations to have been “genuinely valuable, even after allowing for transactions costs and risk”.

Unlike most previous studies, Groth et al. applied the Capital Asset Pricing Model (“CAPM”) to estimate abnormal returns. According to the CAPM, which was developed by Sharpe (1964) and Lintner (1965), a security’s expected return depends on how sensitive it is to market risk. Investors are not compensated for firm-specific risk in the model, as such risk can be diversified away by investing in a sufficient number of securities.

Elton et al.’s (1986) findings support those of Groth et al. However, a key difference between the two articles is that Elton et al. focused on upgrades and downgrades in particular. Upgrades (downgrades) were defined as recommendations that are more bullish (bearish) than the brokerage’s most recent recommendation for the same firm. For example, a “buy” recommendation would be classified as an upgrade if the brokerage’s previous recommendation for the same company was “hold”, “underperform”, or “sell”, and it would be classified as a downgrade if the previous recommendation was “strong buy”.

Looking at 33 brokerages’ recommendations over 33 months, Elton et al. compared the return of an equally-weighted portfolio of stocks that were upgraded to “strong buy” or “buy” with an equally-weighted portfolio of stocks that were downgraded to “sell” or “underperform”. To make the two portfolios comparable, Elton et al. removed companies with the most extreme betas from the portfolio with the most companies, until the two portfolios had virtually the same beta. Elton et al. found the difference between the two portfolios to be about 4.5%, in favour of the portfolio of upgrades, over the month of the recommendation and the following two months. Moreover, the difference was found to be statistically significant at a 5% or better significance level in each of the three months.

Similar to Elton et al., Womack (1996) examined upgrades and downgrades. He found that upgrades (downgrades) to the most (least) favourable recommendation level had an average abnormal post-event stock drift of 2.4% (-9.1%) over one month (six months), both of which were found to be statistically significant at the 5% level. Womack used market capitalization decile returns when calculating abnormal returns, but he noted that “returns are not substantially different using calendar month excess returns derived from the three factor model of Fama and French (1993)”.

Fama and French’s (1992, 1993) three factor model extends the CAPM by adding two additional factors that account for firm size and the relationship between book equity and market equity, respectively. Adding these two factors better isolates “firm-specific components of returns”, according to the authors (Fama and French (1993)).

Carhart (1997) later added a momentum factor to the Fama-French three factor model. This additional factor accounts for a documented higher abnormal Fama-French three factor return of stocks that have a good past performance, relative to stocks with a poor past performance (e.g. Jegadeesh and Titman (1993) and Fama and French (1996)). According to Berk and DeMarzo (2014), the Fama-French-Carhart four-factor model “[…] is currently the most popular choice for the multifactor model”.

Barber et al.’s (2001) findings support those of Groth et al., Elton et al., and Womack. However, unlike these previous studies, they focused on consensus recommendations instead of individual recommendations. Barber et al. found "[…] that purchasing (selling short) stocks with the most (least) favourable consensus recommendations, in conjunction with daily portfolio rebalancing and a timely response to recommendation changes, yield annual abnormal gross returns

[Fama-French-Carhart four-factor model][3] greater than four percent." Nevertheless, the authors also noted that "[…] high trading levels are required to capture the excess returns generated by the strategies analyzed, entailing substantial transactions costs and leading to abnormal net returns for these strategies that are not reliably greater than zero." Their method is described in greater detail in section *4. Method*.

With this strand of literature in mind, we form our first hypothesis as outlined below:

Hypothesis 1: We expect that a portfolio based on the most favourable consensus recommendations for S&P 100 companies should yield positive annual abnormal gross returns, but negative abnormal returns net of transaction costs.

In other words, we expect to re-affirm Barber et al.'s (2001) findings[4]. Next, we look at the possibility of finding a more informative consensus.

2.2 In search of a more informative consensus

2.2.1 Prior earnings forecast accuracy

Based on his findings, Bradshaw (2004) suggested that buy-and-hold investors would earn higher returns by incorporating earnings forecasts, instead of recommendations, in their decisions. In a response to this, both Loh and Mian (2006) and Ertimur et al. (2007) identified an apparent positive relationship between analysts' prior earnings forecast accuracy and the profitability of their recommendations. Consequently, their findings indicate the existence of a more informative consensus – one restricted to recommendations issued by analysts with higher prior earnings forecast accuracy. However, a later study by Hall and Tacon (2010) found it difficult to identify accurate forecasters based on their track record ex ante. Given the finding of Hall and Tacon, a strategy of following accurate earnings forecasters appears difficult to implement in practice. Therefore, we continue the search for a more informative consensus by turning to parallel research on herding behaviour in the next subsection.

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[3] Notably, Barber et al. use the four-factor model "[…] to assess whether any superior returns that are documented are due to analysts' stock-picking ability or to their choosing stocks with characteristics known to produce positive returns" rather than viewing these four as risk factors per se.

[4] Barber et al.'s Table VIII shows "Percentage Gross Monthly and Net Annual Returns Earned by Portfolios Formed on the Basis of Analyst Recommendations and Size, 1986 to 1996". Looking at the results of their large cap (Big) firm subset, they find gross monthly abnormal returns from the Fama-French-Carhart four-factor model of 0.251, 0.212, -0.022, -0.032, and -0.017 for portfolios 1, 2, 3, 4, and 5, respectively. Note that they take a short position in portfolios 3-5. Only portfolio 2 is statistically significant at a 10% level or lower. Net of transaction costs, all returns turn negative.

2.2.2 Herding behavior and boldness

Trueman (1994) argues that "[…] naively calculating a consensus analyst forecast by averaging individual analyst forecasts [like Barber et al.] is inappropriate", because "[…] analysts have a tendency to report forecasts similar to those previously released by other analysts; that is, they exhibit herding behavior". This behavior is, according to Trueman, "[…] undertaken in order to favourably affect investors' assessment of the analyst's forecasting ability".

Furthermore, Trueman noted that "[…] the likelihood of an analyst to herd decreases with his ability to predict earnings". In line with this, Clement and Tse (2005) found that "[…] bold [non-herding] forecasts appear to reflect analysts' relevant private information to a greater extent than herding forecasts".

Later studies have shown that non-herding recommendations are more profitable than herding recommendations. For example, Bagnoli et al. (2010) found that "[…] bold [non-herding] recommendations, which may reflect a greater degree of analyst conviction, are generally more profitable", and Jegadeesh and Kim (2010) found that "[…] the market reaction to analysts' recommendation revision is stronger when the revised recommendations move away from the consensus than when they move towards the consensus."

Given the findings above, we hypothesize that a way to improve the abnormal return of Barber et al.'s method is to calculate consensuses from a subset of analyst recommendations classified as bold using the definitions of Bagnoli et al. (2010) (with minor deviations, as described in *4. Method*) and Jegadeesh and Kim (2010), respectively. Hence, we formulate our second hypothesis as follows:

Hypothesis 2: We expect that restricting the consensus, used to form portfolios, to bold analyst recommendations will result in higher abnormal returns, both gross and net of transaction costs.

In addition, we intend to compare the performance of our two bold subsets against a subset of upgrades and downgrades. This comparison is interesting for two reasons. First of all, it provides a link to previous research, as many studies within the recommendations literature have focused on upgrades and downgrades in particular (e.g. Womack (1996) and Stickel (1995)). Second, Jegadeesh and Kim (2010) found that upgrades and downgrades ("changes") are associated with a greater market reaction than reiterations, i.e. the post-event stock price drift is higher. As such, we expect a consensus based on recommendation changes to outperform the non-filtered consensus.

2.3 Major regulations and events

2.3.1 Regulation Fair Disclosure

Regulation Fair Disclosure ("Reg FD") was adopted by the U.S. Securities and Exchange Commission in August 2000, and it became effective two months later, in October 2000 (Unger (2001)). The purpose of the regulation was to reduce "[…] the selective disclosure of material nonpublic information by issuers to analysts and institutional investors […]" (ibid.). To that end, the regulation forbids management from disclosing "material nonpublic information" to analysts, without also making that information public.

Several studies indicate that Reg FD was effective in reducing disclosure of private information to analysts, e.g. Zitzewitz (2002) and Gintschel and Markov (2004).

Given that Reg FD was effective, we believe that the abnormal return of Barber et al.'s (2001) method should decrease after the regulation came into force. Furthermore, we expect this effect to be particularly pronounced for portfolios based on our two bold subsets, provided that "[…] bold [non-herding] forecasts appear to reflect analysts' relevant private information to a greater extent than herding forecasts" (Clement and Tse (2005)). This forms our third hypothesis, which can formally be expressed as:

Hypothesis 3: Given that Regulation Fair Disclosure was effective, we hypothesize that the abnormal return of our portfolios should decrease after it came into effect. We expect that this effect will be particularly pronounced for our portfolios based on bold recommendations.

In the next subsection, we look at the implications of more recent regulation.

2.3.2 NASD 2711, NYSE 472 and the Global Settlement

We note that more recent regulation – NYSE rule 472 and NASD Rule 2210 in 2002 – and the Global Analyst Research Settlements in 2003 have targeted conflicts of interest among analysts related to investment banking activities. Kadan et al. (2009) found that these regulations have led to "[…] a significant reduction in excess optimism resulting from conflicts of interest between research and investment banking departments".

Importantly, the "reduction in excess optimism" does not make our third hypothesis easier to prove. On the contrary, the effect should make our hypothesis more difficult to prove, ceteris paribus, since only the post-regulation period will benefit from the "reduction in excess optimism".

3. Data

3.1 I/B/E/S

3.1.1 General

The Institutional Brokers' Estimate System ("I/B/E/S") database provides recommendation consensuses at a monthly level. However, in order to repeat Barber et al.'s (2001) method, we need recommendation consensuses on a daily level. Therefore, we have to construct the consensuses ourselves – one for each company and day.

To this end, we gather all sell-side analyst recommendations for U.S. firms that can be found in I/B/E/S's recommendations detail database. We download all available data, i.e. from December 1992 through December 2015, and the following variables: I/B/E/S recommendation code (the recommendation itself, standardized to a scale from one to five, with one signifying "strong buy" and five "sell"), I/B/E/S ticker (permanent company identifier), Analyst masked code (analyst identifier), Announcement date, Announcement time (date and time when the recommendation was issued, respectively), CUSIP codes (financial security identifier), Company name, and Official ticker. All in all, we download 737,672 recommendations.

We then apply the following filters to our dataset. First of all, we drop a lone observation in 1992, as we have no other observation until 29 October, 1993. Second, we remove observations that lack an analyst identifier, reducing the number of observations by 19,705. The analyst identifier is necessary to calculate the consensuses, since only the most recent recommendation of each analyst should be included. Third, we remove companies that lack a CUSIP-code, which reduces the number of observations by 722. Finally, we only keep the latest recommendation when there are multiple recommendations made by the same analyst, on the same day, and for the same company. This reduces the number of observations by 1,677. After applying the filters above, we are left with 715,567 recommendations for 15,576 companies (unique I/B/E/S tickers).

3.1.2 Scope of study

We limit our sample to those companies that were part of Standard & Poor's S&P 100 index, which consists of "100 major, blue chip companies across multiple industry groups" (Standard & Poor (2016a)). Focusing on more liquid S&P 100 stocks makes our proposed strategy easier to implement in practice, both in terms of information processing (i.e. amount and availability of recommendations) and executing transactions for portfolio rebalancing. In addition, the reduced number of companies allows us to manually check, and correct mismatches when merging databases, in a way that would not be possible if we were looking at all 15,576 companies.

3.1.3 Data issues

A concern for our study at hand are the findings of Ljungqvist et al. (2009), who discovered "[…] widespread changes to the historical I/B/E/S analyst stock recommendations database" insofar that "[…] between 6,580 (1.6%) and 97,582 (21.7%) of matched observations are different from one [annual] download to the next". Their study refers to the time period 2000-2007, and they note that "the changes include alterations of recommendations, additions and deletions of records […]". Finally, it appears that these changes are non-random. For example, the authors find that "'Bold' recommendations (those far from consensus) are overrepresented among affected recommendations […]".

In 2007, Thomson supposedly purged the database of most errors. However, Ljungqvist et al. note that the database "[…] continues to include alterations made as a result of brokers' requests for retrospective changes to their buy/hold/sell recommendation scales".

This gives rise to two issues for our study: (i) a lack of comparability with studies using I/B/E/S data downloaded before the purge in 2007 and (ii) a risk of misallocating stocks in our calendar-time portfolios due to faulty historical recommendations. To elaborate on the second issue a bit further, this misallocation could make our second hypothesis easier to prove if bold recommendations are also overrepresented in the alterations that persisted the 2007 purge. However, Ljungqvist et al. does not comment on whether or not this is the case.

Given the above, we encourage future studies to repeat our study using another recommendations database, such as the one provided by Zacks Investment Research, to further validate our findings.

3.2 Compustat

We use Compustat's database of historical index constituents to determine whether or not a company was part of the S&P 100 index on each particular day. Next, we use CUSIP-codes to find the corresponding companies in our I/B/E/S database. While the CUSIP-codes match for most of the companies, we have to manually pair a few of them up based on company names and tickers.

Prior to recent changes, the S&P 100 index only included the most liquid share class for companies with multiple classes[5]. We choose to keep only the first share class listed as a constituent in the index per company, in order to ensure consistency across years. Thus, our dataset has one share per company and 100 constituents per day[6].

Limiting our sample to those companies that have been part of the index at any time between 1993 and 2015 reduces the number of recommendations from 715,567 to 65,418 and the number of unique companies from 15,576 to 206.

Finally, we limit our sample to recommendations for companies that were part of the index on the particular day that the recommendation was announced, or recommendations issued up to 182 days, i.e. six months, before the company entered the index. Six months corresponds to the length of the window that we use to calculate each consensus (see section *4. Method* for further details). Furthermore, we exclude three companies that were removed from the index within the first six months of data (i.e. between November 1993 and April 1994, inclusive). These final limitations reduce the number of recommendations from 65,418 to 43,533 and the number of unique companies from 206 to 203.

3.3 CRSP

We gather the stock data needed to calculate returns and market capitalizations (closing price, shares outstanding, and holding period return) from the Center for Research in Security Prices's ("CRSP") daily stock file database. Since we have already merged Compustat and I/B/E/S and there exists a database with links between CRSP and Compustat, we can simply merge CRSP and I/B/E/S using Compustat as a common identifier. When performing the merge, we look manually at companies with more than one security listed, in order to ensure that we only keep those that pertain to the share class in the index. Furthermore, for companies with several share classes in the index (Google, Comcast, and Twenty-First Century Fox), we only keep the share class that has been in the index the longest, as previously mentioned.

[5] In March 2014, S&P Dow Jones Indices announced a methodology change in its indices allowing for "a multiple share class structure effective with the September, 2015 rebalance". Simultaneously, a revised treatment of Google's recent stock split was declared that meant incorporating both share classes as constituents in the S&P 100 index immediately. As of September 2015, Comcast Corp. and Twenty-First Century Fox Inc. have also had their second share class included (PRNewswire (2015)).

[6] Over the entire sample, May 1994-Dec 2015, there are 10 observations (days) where there is a one day mismatch of an addition and a removal of index constituents, which means that there are 99 instead of 100 constituent companies.

3.4 Factor returns

We download monthly returns for the three Fama-French factors and momentum from Kenneth R. French's data library. To be precise, we download "research factors", as "Fama and French, as well as other academics, use the research factors when explaining the cross-section of returns with the three factor model". These research factors are necessary for calculating abnormal returns. In addition, the risk-free rate at the beginning of each month, derived from the rate on Treasury bills with one month until maturity, is downloaded from the same source.

4. Method

4.1 Barber et al.'s method

4.1.1 Portfolio construction

To test our first hypothesis – that we will find positive (negative) gross (net) abnormal returns of transaction costs when forming a portfolio based on the most favourable consensus recommendations – we repeat Barber et al.'s (2001) method, which is described below.

After applying the steps described in section *3. Data*, we are left with 43,533 recommendations. We use these recommendations to construct a consensus for each company *j* and day τ by summing each analyst *i*'s most recent non-stale rating divided by the total number of analysts with a non-stale recommendation outstanding $n_{j,\tau}$.

$$\boldsymbol{Consensus_{j,t}} = \frac{1}{n_{j,\tau}} \sum_{\tau=1}^{n_{j,\tau}} Recommendation_{i,j,\tau}$$

(Equation 1)

Like Loh and Mian (2006), who also apply Barber et al.'s method, we define stale forecasts as those issued more than 183 days ago. The choice of 183 days, in particular, reflects Womack's (1996) finding that the price drift of recommendations extends for six months[7]. Hence, we only consider the most recent recommendation per analyst *i* for company *j* over the 183-day time span[8]. In other words, if an analyst issues a new recommendation for a company, the new recommendation replaces his or her previous recommendation, and forecasts older than six months are excluded from the consensus. In addition, we only consider recommendations issued before close of trading on day τ. Recommendations issued afterwards are instead incorporated into the next day's consensus.

Having formed consensuses for each company and day, we account for the fact that the stock exchanges are not always open by excluding weekend observations (Saturdays and Sundays), and days when more than 90 of our stocks (keeping in mind that we only look at the S&P 100) have no

[7] Womack finds that "For added-to-buy recommendation changes, the excess return occurs predominantly in the first post-recommendation month. For added-to-sell changes, the excess return accrues over about six months". We use six months as it is the larger of the two.
[8] Note that the consensus is based on recommendations issued up to 182 days prior to, and including, the day observed. Hence, the consensus is the average of the last 183 days of recommendations, including the day observed.

reported data on CRSP. Excluding the days when more than 90 of our stocks lack data is a way to filter out days when the stock exchanges were closed for one reason or another (besides Saturdays and Sundays), e.g. Christmas day and the days following the September 11 attacks. The portfolio is not rebalanced during these non-trading days.

Following the steps above, we allocate S&P 100 companies into three portfolios based on the analyst consensus. This is a slight deviation from Barber et al. (2001), who divide their sample into five portfolios. The rationale for three portfolios is twofold. First of all, Barber et al. find that the difference between the abnormal return of their first and second portfolio (out of five) is quite small for big companies, compared to when looking at medium-sized or small companies[9]. Second, by dividing our companies into fewer portfolios, more companies are allocated to each portfolio, which reduces idiosyncratic exposure. This is especially important for our study, considering our sample consists of relatively few, although large, companies to begin with.

Table 1. Portfolio Definitions

This table shows how we construct three portfolios, based on the analyst consensus for firm *j* on day *τ*. The consensus is calculated for each firm and day as the average of all recommendations issued over the last 183 days, taking only each analyst's most recent recommendation into account. The consensus recommendations are rated on a five-degree scale, with one signifying "strong buy" and five "sell".

Portfolio	Definition
Portfolio 1 – Buy	$1 \leq \text{Consensus}_{j,\tau} \leq 2$
Portfolio 2 – Hold	$2 < \text{Consensus}_{j,\tau} \leq 2.5$
Portfolio 3 – Sell	$2.5 < \text{Consensus}_{j,\tau}$

Having determined which companies belong to which portfolio above, the next step is to determine each company's portfolio weight. Like Barber et al., we construct value-weighted portfolios. That is, the weight of each company *j* in a portfolio on day *τ* equals its market

[9] Barber et al.'s Table VIII shows "Percentage Gross Monthly and Net Annual Returns Earned by Portfolios Formed on the Basis of Analyst Recommendations and Size, 1986 to 1996". Looking at the monthly Fama-French-Carhart four-factor alpha estimates, the second portfolio has a coefficient relative to that of the first portfolio of 57% (0.327/0.575) for small companies, 58% (0.226/0.387) for medium-sized companies, and 84% (0.212/0.251) for big companies.

capitalization divided by the market capitalization of all of the *n* number of companies in portfolio *p*, where all figures are measured at the close of trading on day τ.

$$\boldsymbol{Weight_{j,\tau}} = \frac{MarketCap_{j,\tau}}{\sum_{j=1}^{n_{p,\tau}} MarketCap_{j,\tau}}$$

(Equation 2)

We choose value-weighting instead of equal-weighting for two reasons. First of all, it makes our findings more comparable with Barber et al.'s study. Second, the findings of Plyakha et al. (2014) suggest that a value-weighted portfolio better isolates stock-picking ability. To further elaborate, Plyakha et al. "[…] compare the performance of equal-, value-, and price-weighted portfolios of stocks in the major U.S. equity indices […]" with monthly rebalancing, and they find that the equal-weighted portfolio has a consistently higher Fama-French-Carhart alpha. By considering different rebalancing frequencies, they found that the higher alpha "[…] arises from the monthly rebalancing that is required to maintain equal weights, which is a contrarian strategy". Therefore, "[…] the alpha depends on the rebalancing strategy and not on the particular choice of initial weights" [10].

Like Barber et al., we assume that portfolios are constructed at closing on each day. Therefore, the return of each company *j* within the portfolio on a particular day τ is the return of the next trading day $\tau + 1$. As described in section *3. Data*, we use CRSP's holding period return for our returns, which accounts for dividends and spin-offs (assuming re-investment). The return *r* of portfolio *p* at date $\tau + 1$ is then the sum of its constituent companies' date τ weight (see *Equation 2*) multiplied by their corresponding next day's ($\tau + 1$) return *r*.

$$\boldsymbol{r_{p,\tau+1}} = \sum_{j=1}^{n_{p,\tau}} Weight_{j,\tau} \cdot r_{j,\tau+1}$$

(Equation 3)

[10] As would be expected, given the findings of Plyakha et al. (2014), we find that all Fama-French-Carhart alphas increase when we apply equal-weighting (compare Appendix Table I and Table 3). However, as discussed above, this increase in alpha probably reflects a contrarian strategy.

Now that we have calculated the daily portfolio p returns, $r_{p,\tau}$, the next step is to calculate monthly t returns $R_{p,t}$. This is done by compounding $r_{p,\tau}$ over the n trading days observed within a month.

$$\boldsymbol{R_{p,t}} = \prod_{\tau=1}^{n}(1 + r_{p,\tau}) - 1$$

(Equation 4)

In the following section, we will go through the regressions used to evaluate the performance of the portfolios.

4.1.2 Testing for abnormal returns

In order to calculate abnormal returns, we regress the monthly portfolio excess returns against three asset-pricing models, namely (i) the Capital Asset Pricing Model ("CAPM"), (ii) the Fama and French (1993) three factor model, and (iii) the Fama-French-Carhart four-factor model, which includes price momentum. The standard errors of each regression are estimated with Huber-White sandwich estimators, which allow for heteroscedasticity.

(i) The CAPM:

$$\boldsymbol{R_{p,t}} - \boldsymbol{R_{f,t}} = \alpha_{\mathrm{p}} + \beta_{\mathrm{p}} \cdot (R_{m,t} - R_{f,t}) + \varepsilon_{p,t}$$

(Regression 1)

Where:

$R_{f,t}$ = the risk free rate at the beginning of each month t, derived from the rate on Treasury bills with one month until maturity;

$R_{m,t}$ = the month t return of a value-weighted market portfolio;

α_p = the intercept of the regression, also known as Jensen's alpha;

β_p = the coefficient on the market excess return, also known as the market beta; and

ε_p = the regression residual.

(ii) The Fama-French three factor model:

$$\boldsymbol{R_{p,t}} - \boldsymbol{R_{f,t}} = \alpha_{\mathrm{p}} + \beta_{\mathrm{p}} \cdot (R_{m,t} - R_{f,t}) + s_{\mathrm{p}} \cdot SMB_{\mathrm{t}} + h_{\mathrm{p}} \cdot HML_{\mathrm{t}} + \varepsilon_{p,t}$$

(Regression 2)

Where, in addition to the above:

SMB_t = the return of a value-weighted portfolio of small stocks minus the return of a value-weighted portfolio of large stocks, for each month t; and

HML_t = the return of a value-weighted portfolio of value stocks (high book-to-market equity) minus the return of a value-weighted portfolio of growth stocks (low book-to-market equity), for each month t.

(iii) The Fama-French-Carhart four-factor model:

$$\boldsymbol{R_{p,t}} - \boldsymbol{R_{f,t}} = \alpha_{\mathrm{p}} + \beta_{\mathrm{p}} \cdot (R_{m,t} - R_{f,t}) + s_{\mathrm{p}} \cdot SMB_{\mathrm{t}} + h_{\mathrm{p}} \cdot HML_{\mathrm{t}} + m_{\mathrm{p}} \cdot MOM_{\mathrm{t}} + \varepsilon_{p,t}$$

(Regression 3)

Where, in addition to the above:

MOM_t = the month t return of a value-weighted portfolio of stocks with the highest past returns (prior 11 months), minus the corresponding return of a value-weighted portfolio of stocks with the lowest past returns (prior 11 months).

The constant in each of the regressions corresponds to the abnormal return. Given our first hypothesis – that we will find positive abnormal returns when forming portfolios based on the most favourable consensus recommendations, using the method of Barber et al. (2001) – we expect that this constant will be positive and statistically significant.

As we base each company's consensus on recommendations issued within the past 183 days, we exclude the first six months when running the regressions described above (i.e. we exclude November 1993 through April 1994). Without this exclusion, consensuses for the first six months would be based on less time, and hence fewer recommendations, than later consensuses. For example, a consensus on the first of December 1993 could only be based on one month of historical data, because that is how far back our sample of available data stretches.

4.1.3 Turnover and transaction costs

The first step in calculating portfolio turnover is to find the hypothetical portfolio weight a company would have had on day τ, if there had been no rebalancing since day τ - *1*. This hypothetical weight, denoted $H_{i,\tau}$, is calculated for each stock *i* and day τ according to *Equation 5*. The numerator in the equation contains two parts: $x_{i,\tau-1}$, which corresponds to the portfolio weight of stock *i* on day τ - *1*, and $(1 + r_{i,\tau})$, where $r_{i,t}$ corresponds to the return of stock *i* on day τ. The denominator of *Equation 5* simply equals the sum of the nominator for all stocks *n* that were in in the same portfolio *p* as stock *i* on day τ - *1*.

$$\boldsymbol{H}_{\boldsymbol{i},\tau} = \frac{x_{i,\tau-1} \cdot (1 + r_{i,\tau})}{\sum_{i=1}^{n_{p,\tau-1}} x_{i,\tau-1} \cdot (1 + r_{i,\tau})}$$

(Equation 5)

Having calculated the hypothetical portfolio weights without rebalancing, the next step is to compare them with the actual weights (see *Equation 6*). That is, for each stock that was part of the portfolio on day τ - *1*, we calculate the difference between hypothetical share and actual share in the portfolio, with the difference being limited by a max operator. The max operator ensures that portfolio turnover, which we denote delta (Δ), is only affected by stocks that were sold, either fully or in part. We acknowledge that the proceeds of these sales are used to buy other stocks, and we adjust for this later by our choice of transaction cost estimate.

All of these differences are then summed within each portfolio *p* and day τ to find a portfolio-wide measure of daily turnover, delta (Δ).

$$\boldsymbol{\Delta}_{\boldsymbol{p},\tau} = \sum_{i=1}^{n_{p,\tau-1}} \max\{H_{i,\tau} - A_{i,\tau}, 0\}$$

(Equation 6)

Finally, we multiply the average daily portfolio turnover by 250 (an approximation of the number of trading days in a year) to get an annual turnover for each portfolio. This annual turnover is then multiplied with a transaction cost estimate, reflecting the sum of both the cost to buy and the cost to sell a stock. Like Barber et al., we use a cost estimate from Keim and Madhavan's (1998) study. To be precise, we use a cost estimate of 0.57 percent, which represents trading in the largest companies, by market capitalization.

4.2 Classification and creation of subsets

To test our second hypothesis – that we will find higher abnormal returns when applying Barber et al.'s method to only a subset of all recommendations, namely those that are non-herding ("bold") – we construct two subsets of bold recommendations, according to the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010).

4.2.1 Jegadeesh and Kim bold subset

Jegadeesh and Kim (2010) classify recommendations as bold if the absolute distance of a recommendation made by analyst *i* for company *j* on date *t* compared to the consensus of the same company *j* at date *t – 1* is larger than the absolute distance of the previous recommendation made by analyst *i* for company *j* at date τ compared to the consensus at date $\tau - 1$. In simpler terms, this definition of bold captures recommendations that are more bold (relative to the consensus) than the analyst's most recent recommendation for the same company.

$$\boldsymbol{JBold_{i,j,t}} = 1 \quad \text{IF} \quad \left| \frac{Recommendation_{i,j,t} - Consensus_{j,t-1}}{Recommendation_{i,j,\tau} - Consensus_{j,\tau-1}} \right| > 1$$

(Equation 7)

To test our second hypothesis, we only keep recommendations that are classified as bold, according to *Equation 7*. This reduces the number of recommendations from 43,533 to 14,736. Based on this subset of recommendations, henceforth referred to as "JBold" for brevity, we repeat the method of forming portfolios and calculating abnormal returns, as described in section *4.1 Barber et al.'s method*.

4.2.2 Bagnoli et al. bold subset

Bagnoli et al. (2010) classify recommendations as bold if the absolute distance between a recommendation issued by analyst *i* for company *j* on date *t* and the consensus on the day before, i.e. *t – 1*, is larger than one[11].

[11] Bagnoli et al. go further and then use this dummy variable as a basis for an average for each analyst, company, and year. As we focus on recommendations, we do not take this second step.

$$\boldsymbol{BBold_{i,j,t}} = 1 \quad IF \quad \left|Recommendation_{i,j,t} - Consensus_{j,t-1}\right| > 1$$

(Equation 8)

To test our second hypothesis, we only keep recommendations that are classified as bold, according to *Equation 8*. This reduces the number of recommendations from 43,533 to 11,428. Based on this subset of recommendations, henceforth referred to as "BBold" for brevity, we repeat the method of forming portfolios and calculating abnormal returns, as described in section *4.1 Barber et al.'s method*.

4.2.3 Changes subset

Due to the prominence of upgrades and downgrades in previous literature, we also include a subset of such recommendations for comparison. We refer to this subset as "Changes". The Changes subset consists of recommendations that differ from the previous recommendation issued by analyst *i* for company *j* at date τ. In other words, the subset consists of all recommendations that are not reiterations, but rather upgrades or downgrades.

$$\boldsymbol{Changes_{i,j,t}} = 1 \quad IF \quad \left|Recommendation_{i,j,t} - Recommendation_{i,j,\tau-1}\right| > 0$$

(Equation 9)

To form the Changes subset, which will be used for comparison, we only keep recommendations that are classified as changes, according to *Equation 9*. This reduces the number of recommendations from 43,533 to 22,991. Based on this subset of recommendations, we repeat the method of forming portfolios and calculating abnormal returns, as described in section *4.1 Barber et al.'s method*.

4.3 Testing for differences after Regulation Fair Disclosure

To test our third hypothesis – that the abnormal return of recommendations has decreased after the implementation of Regulation Fair Disclosure, particularly for our bold subsets – we introduce a dummy variable that separates the time periods before (dummy variable equals one) and after (dummy variable equals zero) the regulation in question. These two time periods correspond to May 1994-Oct 2000 and Nov 2000-Dec 2015, respectively.

We also introduce interaction terms, which are the dummy multiplied with each of the factor returns in the three asset-pricing models described in section *4.1.2 Testing for abnormal returns*. This allows the factor coefficients to vary between the two periods.

(i) The CAPM:

$$\boldsymbol{R_{p,t}} - \boldsymbol{R_{f,t}} = \alpha_{\mathrm{p}} + \beta_{\mathrm{p}} \cdot \left(R_{m,t} - R_{f,t}\right) + \mathrm{PreRFD} + \mathrm{PreRFD} * \beta_{\mathrm{p}} \cdot (R_{m,t} - R_{f,t}) + \varepsilon_{p,t}$$

(Regression 5)

(ii) The Fama-French three-factor model:

$$\begin{aligned}\boldsymbol{R_{p,t}} - \boldsymbol{R_{f,t}} = {} & \alpha_{\mathrm{p}} + \beta_{\mathrm{p}} \cdot \left(R_{m,t} - R_{f,t}\right) + s_{\mathrm{p}} \cdot SMB_{\mathrm{t}} + h_{\mathrm{p}} \cdot HML_{\mathrm{t}} + \mathrm{PreRFD} + \mathrm{PreRFD} \cdot \beta_{\mathrm{p}} \\ & \cdot \left(R_{m,t} - R_{f,t}\right) + \mathrm{PreRFD} \cdot s_{\mathrm{p}} \cdot SMB_{\mathrm{t}} + \mathrm{PreRFD} \cdot h_{\mathrm{p}} \cdot HML_{\mathrm{t}} + \varepsilon_{p,t}\end{aligned}$$

(Regression 6)

(iii) The Fama-French-Carhart four-factor model:

$$\begin{aligned}\boldsymbol{R_{p,t}} - \boldsymbol{R_{f,t}} = {} & \alpha_{\mathrm{p}} + \beta_{\mathrm{p}} \cdot \left(R_{m,t} - R_{f,t}\right) + s_{\mathrm{p}} \cdot SMB_{\mathrm{t}} + h_{\mathrm{p}} \cdot HML_{\mathrm{t}} + m_{\mathrm{p}} \cdot MOM_{\mathrm{t}} + \mathrm{PreRFD} \\ & + \mathrm{PreRFD} \cdot \beta_{\mathrm{p}} \cdot (R_{m,t} - R_{f,t}) + \mathrm{PreRFD} \cdot s_{\mathrm{p}} \cdot SMB_{\mathrm{t}} + \mathrm{PreRFD} \cdot h_{\mathrm{p}} \cdot HML_{\mathrm{t}} \\ & + \mathrm{PreRFD} \cdot m_{\mathrm{p}} \cdot MOM_{\mathrm{t}} + \varepsilon_{p,t}\end{aligned}$$

(Regression 7)

Given that our third hypothesis is true, we expect that this dummy variable will be positive and statistically significant, at least for the portfolios based on bold consensus recommendations.

5. Results

In this section, we present our results, with a focus on the buy portfolio. There are two reasons as to why we narrow our main focus to the buy portfolio. First of all, Barber et al. only find economically significant results for portfolios 1 and 2 (corresponding to our buy portfolio) when looking at a subset of big firms, and only the abnormal return of their portfolio 2 is statistically significant at a 10% level or better, out of all their five portfolios. Second, taking short positions may be difficult in practice due to several constraints (see e.g. Jones and Lamont (2002)). These constraints are reasonably more pronounced when rebalancing frequently, as we intend to do, due to the associated requirement of borrowing stock on short notice. Nevertheless, we still report our findings for the hold and sell portfolios in **Appendix Table III**.

5.1 Descriptive statistics

Table 2 reports descriptive statistics for our sample. The observant reader will notice that the number of recommendations add up to 41,317, whereas we have previously stated that our sample consists of 43,533 recommendations. There are two reasons for this discrepancy. First of all, the table only considers recommendations for companies that were in the S&P 100 on the day of the recommendation, whereas the earlier stated figure includes recommendations issued up to 182 days before the day a company entered the index (these days are needed to calculate the consensus). Second, the table only shows whole years (beginning with 1994), whereas the earlier stated figure also includes recommendations from November and December 1993.

The second column of **Table 2** shows the number of unique companies per year. It is important to note that while our sample is based on the S&P 100 index, which consists of 100 companies at any one time[12], the number of unique companies in any particular year can exceed 100 if a constituent company was replaced. On average, there are 105 unique companies per year. In other words, five companies have been replaced in the index per year, on average. Two years feature particularly many replacements: 2000 (16 replacements) and 2008 (14 replacements). These high numbers are explained by the dot-com bubble and the 2008 financial crisis, respectively.

The third column reports the minimum and maximum market capitalizations for every year. The highest market cap in our sample belongs to Apple ($775 billion on 23 February 2015),

[12] Over the entire sample, May 1994-Dec 2015, there are 10 observations (days) where there is a one day mismatch of an addition and a removal of index constituents, which means that there are 99 instead of 100 constituent companies.

whereas the smallest one belongs to Lehman Brothers ($146 million on 15 September 2008). Looking at the average value for all years, the minimum market cap is about one percent of the maximum market cap. However, it should be noted that at least some of the minimum values belong to companies that were in distress, e.g. Lehman Brothers before facing bankruptcy during the 2008 financial crisis, and Delta Air Lines [sic] at the time of its Chapter 11 bankruptcy in 2005. Importantly, companies such as these are unlikely to have favourable recommendations and are therefore improbable to fall into the buy portfolio that we mainly focus on. Thus, the portfolio weights (remember that our portfolios are value-weighted) are unlikely to be as lopsided as the difference between minimum and maximum market caps suggests.

The fourth column shows the number of recommendations per year for all companies in the S&P 100 index. On average, there are about 1,900 such recommendations per year. We notice that the year 2002 has the highest number of recommendations by far: 3,273. This number represents a 76% increase from the previous year. Barber et al. (2007) also find exceptionally many recommendations in 2002, which they explain "[…] is due, in large part, to the reissuance of recommendations just before September 9 [2002], the effective date for implementation of National Association of Securities Dealers (NASD) Rule 2711 which, among other things, requires every securities firm to disclose in each of its research reports the distribution of the firm's ratings across buys, holds, and sells."

The most recent year, 2015, has the fewest number of recommendations: 1,298. A possible explanation for this low number is that it reflects a relatively low research budget, provided that the downward trend in equity research budgets following the financial crisis, which Frost Consulting found in a 2013 report, has continued[13].

Columns five through seven report the share of recommendations that are classified as bold or changes each year, according to each of our three definitions. It is important to note that these definitions are neither mutually exclusive nor collectively exhaustive, and therefore they do not necessarily sum to 100 percent. Depending on the year, between 31% and 40% of all recommendations are classified as bold, according to Jegadeesh and Kim's (2010) definition. Using our simplified version of Bagnoli et al.'s (2010) definition of bold, between 19% and 29% of

[13] Frost Consulting found that equity research budgets have declined by about 40% from the financial crisis to 2013 (Edison (2014)).

recommendations are classified as such per year. Finally, between 47% and 66% of all recommendations are classified as changes, i.e. upgrades and downgrades.

Columns eight and nine of **Table 2** report how the bold subsets overlap with the changes subset. On average, 29% of all upgrades and downgrades are also classified as bold according to Bagnoli et al.'s definition. The corresponding figure for the Jegadeesh and Kim subset is 49%. In other words, less than half of all changes are also classified as bold. Moreover, the two bold subsets differ from the changes subset insofar that they also include reiterations (these make up 33% of the Bagnoli et al. subset and 24% of the Jegadeesh and Kim subset[14]).

Table 2. Descriptive Statistics on Recommendations for S&P 100 Companies, 1994-2015

This table reports descriptive statistics on recommendations for companies listed as constituents in the S&P 100 index over the period 1994-2015. The recommendation data was gathered from I/B/E/S, and the S&P 100 index constituents from Compustat. The total number of firms that are part of the S&P 100 index in a particular year is shown in column (2). The minimum and maximum market capitalizations, denoted in millions of dollars, are reported in column (3). This refers to the lowest and highest observation of any S&P 100 company in a particular year. The number of recommendations in column (4) takes all recommendations into account, whereas columns (5-7) shows the percentage of recommendations that are part of the subsets BBold, JBold, and Changes, respectively. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. All of these subsets are described in greater detail in *section 4. Method*. Columns (8-9) report the percentage of changes that are also classified as bold. This corresponds to the number of recommendations that are classified both as bold and changes, divided by the total number of changes. The values within parentheses in columns (8-9) are the share of bold recommendations that are not reiterations. The mean and median number of analysts issuing recommendations for S&P 100 companies are shown in columns (10-11), as is the mean and median number of companies covered by each analyst following at least one S&P 100 company in a year in columns (12-13). Columns (14-15) report the number of brokerage houses and analysts, respectively, with at least one S&P 100 company recommendation in a particular year. Finally, the average rating (on a five-degree scale, with one signifying "strong buy" and five "sell") of all recommendations for S&P 100 companies is found in column (16).

[14] These figures are simply 100 percent minus the share of bold recommendations classified as changes (see the figures in parentheses in Table 2 columns eight and nine).

Year	No. of firms[a]	Min (Max) market cap $M	No. of firm recommendations	Firm recommendations per subset[b], %			Changes classified as bold (vice versa), %		Analysts per S&P 100 firm		Firms covered per analyst[c]		No. of brokers	No. of analysts[d]	Average rating
				BBold	JBold	Changes	BBold	JBold	Mean	Median	Mean	Median			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1994	102	188 (93,600)	2,024	27	31	52	36 (70)	52 (89)	12.70	13	10.84	9	98	638	2.33
1995	102	185 (121,000)	2,125	26	36	66	32 (79)	48 (87)	12.24	12	9.74	8	99	686	2.32
1996	103	860 (173,000)	1,648	27	38	65	30 (71)	49 (83)	11.02	11	8.93	8	114	658	2.24
1997	102	865 (247,000)	1,538	25	35	60	30 (72)	50 (85)	10.88	10	8.31	7	128	688	2.24
1998	106	686 (358,000)	1,867	23	35	64	26 (73)	46 (85)	11.84	11	8.24	7	122	738	2.21
1999	106	748 (615,000)	1,759	24	36	60	27 (67)	49 (82)	12.03	11	7.96	7	115	778	2.08
2000	116	214 (601,000)	1,602	22	36	58	24 (63)	51 (83)	10.38	10	7.15	6	124	739	2.05
2001	106	270 (530,000)	1,862	23	37	57	25 (62)	50 (78)	12.28	11	6.93	6	113	851	2.18
2002	101	427 (413,000)	3,273	23	37	52	28 (62)	50 (70)	19.11	18	9.50	9	120	1045	2.42
2003	101	198 (347,000)	2,478	28	38	53	33 (63)	50 (70)	16.50	16	8.52	7	130	918	2.52
2004	101	368 (396,000)	1,843	26	36	54	33 (68)	50 (76)	13.66	13	8.16	7	125	794	2.48
2005	107	200 (410,000)	1,588	27	37	60	32 (71)	48 (79)	11.21	11	7.40	6	128	727	2.48
2006	105	1,640 (459,000)	1,608	25	37	56	31 (70)	47 (71)	11.20	10	7.87	7	117	687	2.48
2007	106	5,370 (527,000)	1,709	24	37	55	31 (69)	49 (72)	11.82	12	8.00	7	119	678	2.50
2008	114	146 (513,000)	2,212	28	40	56	34 (67)	50 (71)	13.21	13	8.41	7	127	719	2.45
2009	106	1,730 (415,000)	2,125	29	38	56	31 (60)	49 (73)	15.20	15	8.58	7	149	823	2.44
2010	101	3,260 (370,000)	1,889	26	35	52	28 (55)	45 (68)	14.43	13	7.61	6	166	778	2.31
2011	104	6,470 (439,000)	1,983	24	36	58	26 (60)	44 (72)	14.05	13	7.84	6	150	819	2.31
2012	106	6,350 (658,000)	1,811	22	36	59	25 (67)	45 (75)	12.92	12	7.59	6	143	767	2.53
2013	104	17,400 (516,000)	1,542	23	38	53	27 (64)	50 (71)	12.13	12	7.64	6	131	688	2.42
2014	101	20,800 (698,000)	1,533	19	34	47	25 (60)	48 (66)	12.47	12	7.70	6	126	687	2.39
2015	106	11,800 (775,000)	1,298	21	39	56	27 (72)	52 (75)	10.43	10	7.85	7	126	656	2.40
Average All Years	105	3,644 (439,755)	1,878	25	36	57	29 (67)	49 (76)	13	12	8	7	126	753	2.35

[a] By subtracting 100 from each year in column (2), and then adding back the original 100, one gets 206 companies. Out of these, 204 are unique (two are double-counted as they return to index in later years). However, one of them is only part of the index prior to May 1994, which means that our sample has 203 unique companies – as mentioned in section 3. Data.

[b] The definitions used to create the subsets are not mutually exclusive, hence there may be overlaps and columns (5), (6) and (7) do not sum to 100 percent.

[c] Based on the full database, including all companies available from I/B/E/S 1994-2015, for the analysts that have issued recommendations for a S&P 100 company in that year.

[d] An analyst may follow several firms, hence the mean number of analysts per firm (10) multiplied by the number of firms (2) does not necessarily equal the number of analysts (15).

The tenth column shows the average number of analysts per firm and year in our sample. This ranges from about 10 to 19, depending on the year, with an average of about 13. Our average is more than twice as high as the value in Barber et al.'s (2001) sample (4.74 analysts per firm). This discrepancy is explained by the fact that our sample consists solely of large companies, which understandably attract greater interest, whereas Barber et al. looked at companies of all sizes.

As can be seen in the twelfth column, the analysts in our sample cover an average of about 7 to 11 companies per year (including companies not in the S&P 100 index), with an average of about 8 across all the years. This is lower than the number reported by Barber et al. As before, we believe that the explanation for this discrepancy is that our sample consists solely of large companies. A possible explanation could, for example, be that following larger companies is more time-consuming (e.g. due to the complexity of large, possibly multinational, businesses), and thus limiting the number of companies that can be followed.

Figure 1 shows the gross geometric mean annual return for each of our three portfolios (buy, hold, and sell) and each of our four datasets (the two bold definitions, changes, and all recommendations). The portfolio returns assume a long position in the buy portfolio and short positions in the hold and sell portfolios, following Barber et al. For comparison, we have also included the corresponding figure for the S&P 100 index.

We notice that the buy portfolio has a positive gross geometric mean annual return for each of our four datasets. Moreover, all of that portfolio's annual returns exceed that of the S&P 100 index. On the other hand, the hold and sell portfolios all have negative gross geometric mean annual returns, when taking their short positions into account. In conclusion, the above supports our focus on the buy portfolio.

Figure 1. Mean Annual Raw Return per Dataset and Portfolio, May 1994-Dec 2015

This figure illustrates the geometric mean annual raw return earned by portfolios 1-3, formed on the basis of consensus analyst recommendations, in the period May 1994-Dec 2015. Moreover, we report returns for all recommendations (Ordinary) and three subsets (BBold, JBold, and Changes). BBold and Jbold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in *section 4. Method*. For comparison, we also report the corresponding figures of the S&P 100 index. Note that the gross returns assume taking a long (short) position in portfolio 1 or S&P 100 (portfolio 2 or 3), in accordance with Barber et al. (2001). Monthly returns of the S&P 100 index have been downloaded from Yahoo Finance.

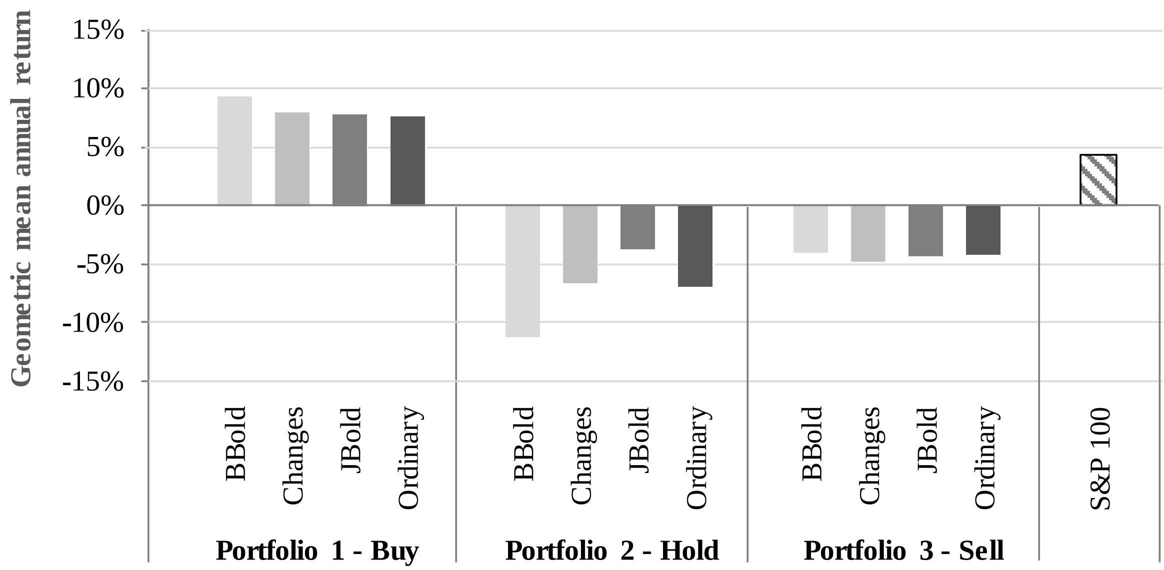


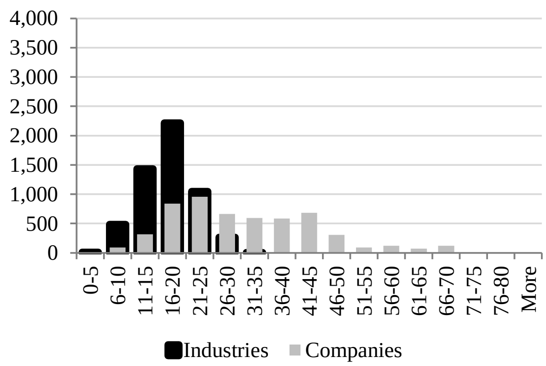
Figure 2 reports how many companies and industries each of our four buy portfolios contains per day. The first of the four buy portfolios was constructed using consensuses based on all recommendations, whereas the other three were constructed using consensuses based on a subset of all recommendations – those classified as bold or changes.

As can be seen in **Figure 2**, the two buy portfolios based on the Jegadeesh and Kim, and Bagnoli et al. definitions of bold have the highest number of industries and companies per day on average. The Jegadeesh and Kim (Bagnoli et al.) buy portfolio consists of 42 (41) companies and 21 (21) industries per day on average, whereas the buy portfolio based on all recommendations (upgrades and downgrades only) consists of 32 (37) companies and 17 (19) industries per day on average. At first glance, it might seem surprising that the bold buy portfolios have about ten more companies per day on average than a buy portfolio based on all recommendations. After all, the bold portfolios are based on fewer recommendations.

Figure 2. Histogram of Portfolio 1's Composition per Dataset, May 1994-Dec 2015

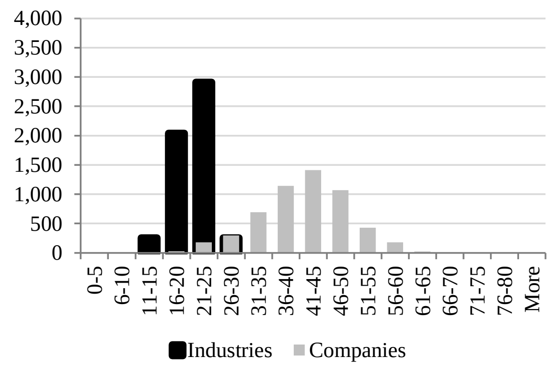
This figure shows the composition of portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies in the period May 1994-Dec 2015. The y-axis shows the frequency, corresponding to the number of days where a certain amount of industries or companies are included in the portfolio, as shown in the x-axis. An industry is defined as a unique two-digit SIC-code. **Panel A** reports the composition using all available recommendations (Ordinary). **Panel B** reports the composition using recommendations from the subset JBold, which defines recommendations as bold if they deviate more (relative to the consensus) than the analyst's most recent recommendation for the same company. **Panel C** reports the composition using recommendations for companies from the subset BBold, which defines recommendations as bold if the absolute distance to last day's consensus is greater than one level. **Panel D** reports the composition using recommendations from the subset Changes, which consists of upgrades and downgrades.

Panel A. Frequency of Portfolio 1 – Ordinary



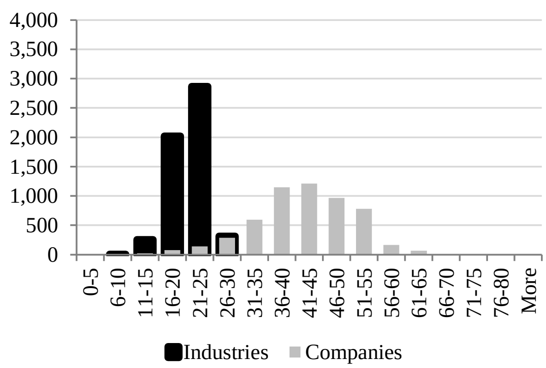
Min	5	8
Max	31	71
Avg	17.21	31.50

Panel B. Frequency of Portfolio 1 – JBold



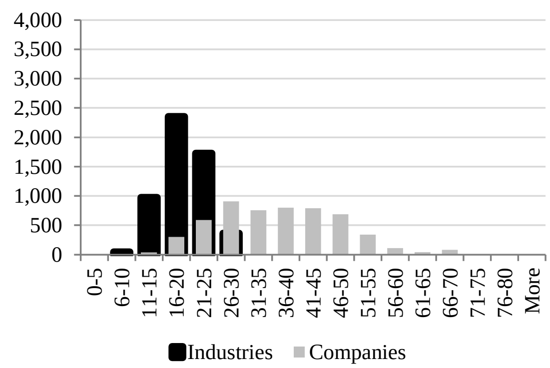
Min	9	14
Max	27	64
Avg	20.96	42.09

Panel C. Frequency of Portfolio 1 – BBold



Min	12	18
Max	28	66
Avg	20.89	41.45

Panel D. Frequency of Portfolio 1 – Changes



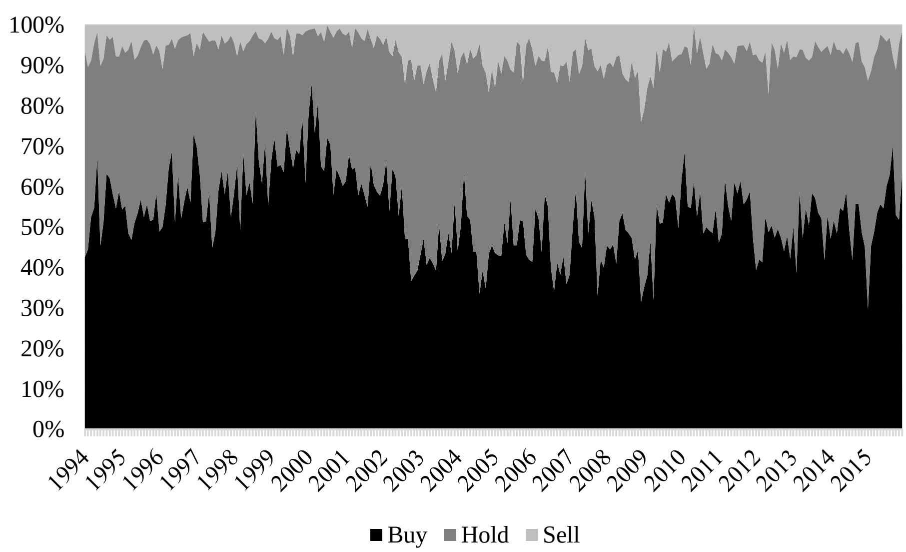
Min	8	13
Max	30	72
Avg	19.22	36.72

We believe that the above could be explained by the lower likelihood of the two bold definitions to capture recommendations in the middle of the scale, given that the consensus (which both definitions take into account) is typically around the middle (see average rating in **Table 2** column 16). By excluding these recommendations when calculating new consensuses based on a subset of bold recommendations, the new consensuses are less likely to be close to the middle of the scale, and therefore companies are more likely to fall into the buy or sell portfolios.

Looking at **Table 2** column 16 again in greater detail, we notice that the average recommendation seemingly became less optimistic beginning in 2002. **Figure 3**, which shows the distribution of different ratings per year, indicates the same trend. This trend can be explained by NYSE rule 472 and NASD Rule 2210, both of which were adopted in 2002 and targeted conflicts of interest among analysts related to investment banking activities. Indeed, Kadan et al. (2006) found that these regulations have led to "[…] a significant reduction in excess optimism resulting from conflicts of interest between research and investment banking departments".

Figure 3. Monthly Distribution of Recommendations for S&P 100 Companies, 1994-2015

This figure shows the monthly distribution of analyst recommendations for S&P 100 companies, over the period 1994-2015. The recommendation data was gathered from I/B/E/S, and the S&P 100 index constituents from Compustat. Recommendations are rated on a five-degree scale, with one signifying "strong buy" and five "sell". In the figure, we group ratings one and two into "buy" and four and five into "sell", while we refer to a rating of three as "hold".



Looking at **Figure 3**, we also note that the share of buy recommendations generally increased until the dot-com bubble burst. Subsequently, the share of buy recommendations decreased substantially, mainly to the benefit of hold recommendations.

Figure 4. Cumulative Raw Return of Portfolio 1 per Dataset, May 1994-Dec 2015

This figure illustrates the development of cumulative raw returns earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies in the period May 1994-Dec 2015. Portfolio 1 contains companies with the most favourable consensus recommendations. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. We report portfolio returns derived from a dataset of all recommendations (Ordinary) and three subsets (BBold, JBold, and Changes). BBold and Jbold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in *section 4. Method*. For comparison, we also report the corresponding figures of the S&P 100 index. Monthly returns of the S&P 100 index have been downloaded from Yahoo Finance.

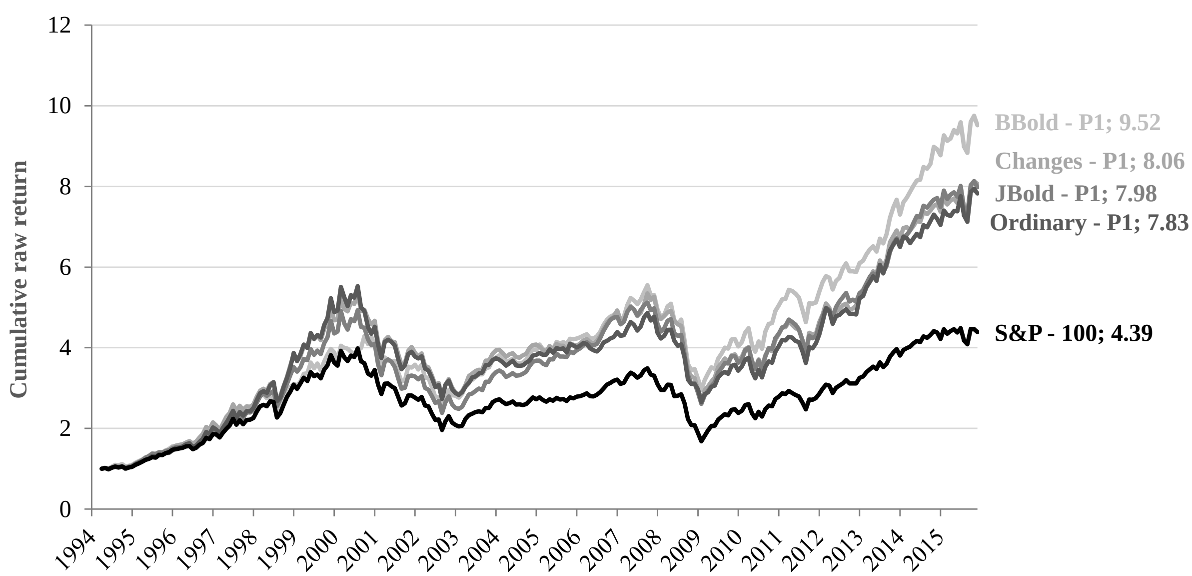


Figure 4 shows the cumulative raw return per year for the buy portfolio. We notice that the buy portfolio based on all recommendations outperforms the S&P 100 index over the whole time period, in support of our first hypothesis (this can also be seen in **Figure 1**). The support for our second hypothesis is mixed: The buy portfolio based on the Bagnoli et al. definition of bold

performs better than the buy portfolio based on all recommendations, but the buy portfolios based on changes and Jegadeesh and Kim's definition of bold only perform marginally better than the buy portfolio based on all recommendations. Finally, the bold buy portfolios (especially the one based on Bagnoli et al.'s definition of bold) appear to have performed worse than the buy portfolio based on all recommendations before Regulation Fair Disclosure, whereas the opposite appears to be true after Regulation Fair Disclosure. This is at odds with our third hypothesis. In summary, the descriptive statistics provide support for our first hypothesis, mixed support for our second hypothesis, and no support for our third hypothesis.

However, it is important to note that the analysis above does not reflect that the risk of the portfolios can differ from the market (the S&P 100 benchmark) and from each other. In order to take this into account, we run CAPM, Fama-French three factor, and Fama-French-Carhart four-factor regressions in the next section.

5.2 Regressions

5.2.1. Coefficients

The individual regressions, including factor coefficients, can be found in **Appendix Table II**. The three panels all look at the buy portfolio, but they differ insofar that they look at different time periods: Panel A refers to the whole time period (May 1994-Dec 2015), the period before Regulation Fair Disclosure (May 1994-Oct 2000) is shown in Panel B, and the period after Regulation Fair Disclosure (Nov 2000-Dec 2015) in Panel C. **Table 3**, in the next section, then summarizes the most important findings from our regressions, namely: alphas (regression intercepts). Additionally, **Table 3** reports the annual turnover of each of the buy portfolios and their corresponding alphas net of trading costs.

As can be seen in **Appendix Table II**, the coefficient on the market excess return portfolio is consistently close to one and highly statistically significant (1%). This finding is not surprising, considering that our sample is based on the S&P 100, which is essentially the market index[15]. Recall that the market index has a beta of one, by definition. Furthermore, the fact that our sample consists solely of large companies explains why the coefficient on the small minus big portfolio,

[15] As of April 29, the S&P 100 and S&P 500 index fact sheets report a total market cap of $11,939,376.63 and $18,917,896.38 million, respectively (Standard & Poor (2016a) and ibid. (2016b)). This implies that the S&P 100 index constituents represent about 63% of the S&P 500 index market capitalization, and around 50% of the total US market.

which is supposed to capture a small company premium, is consistently negative and highly statistically significant (1%).

Looking at **Appendix Table II** again, we notice that the coefficient on the momentum factor, while statistically significant in some cases, is generally small in magnitude compared to the other coefficients. The exception is the Bagnoli et al. buy portfolio before Regulation Fair Disclosure (see **Appendix Table II** Panel B); its momentum coefficient is of a similar magnitude to the loading on the small minus big portfolio and highly statistically significant (1%). Moreover, the negative sign on the coefficient implies that the Bagnoli et al. buy portfolio had a contrarian component before Regulation Fair Disclosure (a contrarian strategy being the opposite of a momentum strategy).

A possible explanation for the contrarian component of the Bagnoli et al. buy portfolio is the finding by Jegadeesh et al. (2004) that sell-side analysts prefer stocks with high momentum. This effect should, ceteris paribus, lead to a more (less) optimistic consensus for high (low) momentum stocks. Consequently, buy recommendations for these high (low) momentum stocks should become relatively less (more) likely to be classified as bold when using Bagnoli et al.'s definition, since the definition looks at the distance to the relatively more (less) optimistic consensus.

Jegadeesh et al. also found that analysts prefer high growth stocks. The same reasoning as above could therefore explain why all buy portfolios except the one for the Bagnoli et al. subset have a negative value factor coefficient, whereas the Bagnoli et al. portfolio has a value factor coefficient close to zero (see **Appendix Table II**).

5.2.2. Alphas

Given our first hypothesis[16], we expect that the alpha from the Fama-French-Carhart four-factor model will be positive and statistically significant when looking at the buy portfolio based on all recommendations. Furthermore, we expect that this alpha will become negative once we subtract transaction costs. However, as can be seen in **Table 3** below, the alpha for our buy portfolio based on all recommendations, referred to as "Ordinary", is not statistically significant at any reasonable significance level in neither the whole period, nor the pre-Regulation Fair Disclosure period, nor the post-regulation period. Moreover, the Fama-French-Carhart alpha becomes negative in both

[16] Hypothesis 1: We expect that a portfolio based on the most favourable consensus recommendations for S&P 100 companies should yield positive annual abnormal gross returns, but negative abnormal returns net of transaction costs.

the whole period and the post-Regulation Fair Disclosure period when we subtract trading costs. The alpha remains positive when looking at the pre-Regulation Fair Disclosure period, but it is not statistically significant at any reasonable significance level.

Given our second hypothesis[17], we expect that that the alpha from the Fama-French-Carhart four-factor model will be positive and statistically significant when looking at the buy portfolio based on recommendations classified as bold according to Jegadeesh and Kim (2010) and our modified version of Bagnoli et al. (2010), respectively. Moreover, we expect that the alphas will remain positive and statistically significant once we subtract transaction costs.

As can be seen in **Table 3**, we do not find alphas that are positive and statistically significant at any reasonable significance level for the Jegadeesh and Kim subset. We do find positive and statistically significant alphas for the Bagnoli et al. subset, however. Looking at the whole period, we find an economically significant annualized alpha of about 2.2% that is also statistically significant at the 10% level. The annualized alpha is considerably higher when looking at the pre-Regulation Fair Disclosure period in isolation: about 7.8% and statistically significant at the 5% level. Looking at the post-Regulation Fair Disclosure period in isolation, the annualized alpha is statistically insignificant at any reasonable significance level.

Once we subtract transaction costs, the annualized alpha for the Bagnoli et al. subset becomes negative when looking at the whole period. When looking at the pre-Regulation Fair Disclosure period in isolation, the annualized alpha decreases from about 7.8% to 4.5%. More importantly, once we subtract transaction costs, the alpha is no longer statistically significant (at any reasonable significance level).

[17] Hypothesis 2: We expect that restricting the consensus, used to form portfolios, to bold analyst recommendations will result in higher abnormal returns, both gross and net of transaction costs.

Table 3. Percentage Annual Abnormal Returns of Portfolio 1 per Dataset and Period

This table shows the annual abnormal return earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies, over the period May 1994-Dec 2015. Portfolio 1 contains companies with the most favourable consensus recommendations. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section *4. Method*. The percentage raw returns in column (1) are calculated as the geometric mean annual return earned by portfolio 1 for each subset and period. The annualized CAPM alpha (i.e. intercept) in column (2) is estimated from a time-series regression of the monthly portfolio 1 excess return on the market excess return, which is then multiplied by 12 to derive an annualized alpha. The annualized Fama-French ("FF") three factor model alpha (i.e. intercept) in column (3) is estimated by adding the return of a zero-investment size portfolio ("SMB") and that of a zero-investment book-to-market portfolio ("HML") as independent variables. The annualized Carhart ("FFC") four-factor model alpha (i.e. intercept) in column (4) is estimated by adding the return of a zero-investment price momentum portfolio ("MOM") as an independent variable. Annual turnover in column (5) is calculated as the average percentage of the portfolio's holdings that have been sold from one trading day to another, multiplied by the number of trading days per year (approximately 250). The net annual return, found in columns (6-8), is then calculated by subtracting the annual turnover multiplied by the round-trip cost of a trade from the corresponding alphas in columns (2-4). The round-trip cost is set to 0.57 percent, in accordance with Keim and Madhavan's (1998) estimate for the largest companies by market capitalization. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French's data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	9.962	0.936	1.764	1.044	687	-2.980**	-2.152*	-2.872**
JBold subset	10.060	0.960	1.500	1.068	582	-2.357**	-1.817*	-2.249**
BBold subset	10.959	2.304	2.304*	2.196*	505	-0.575	-0.575	-0.683
Changes subset	10.112	1.092	1.596	1.092	601	-2.334*	-1.830*	-2.334**
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	27.718	4.668*	4.356*	3.840	639	1.026	0.714	0.198
JBold subset	26.024	4.260	3.852*	3.168	585	0.926	0.518	-0.167
BBold subset	25.092	6.504*	4.440	7.776**	573	3.238	1.174	4.510
Changes subset	27.868	5.736**	5.124**	5.508**	642	2.077	1.465	1.849
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	3.129	-1.308	0.228	-0.132	714	-5.378***	-3.842***	-4.202***
JBold subset	3.852	-0.720	0.432	0.240	587	-4.066***	-2.914***	-3.106***
BBold subset	5.401	0.852	1.824	1.464	482	-1.895	-0.923	-1.283
Changes subset	3.278	-1.224	-0.108	-0.372	590	-4.587***	-3.471***	-3.735***

Significance levels are based on monthly returns and their corresponding robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

While it is not part of our second hypothesis, we also include a portfolio constructed from upgrades and downgrades only (this is referred to as "Changes" in all of the tables) for comparison. As can be seen in **Table 3**, its Fama-French-Carhart alpha is statistically significant (5%) in the pre-regulation period. Moreover, it is economically significant (5.5% on an annual level) in this period, but of a somewhat smaller magnitude than the portfolio based on the Bagnoli et al. subset (7.8% on an annual level). As was the case for the Bagnoli et al. portfolio, the alpha is no longer statistically significant at any reasonable significance level once we subtract transaction costs.

Table 4. The Effect of Regulation Fair Disclosure on the Percentage Monthly Abnormal Returns of Portfolio 1 per Dataset

This table shows the monthly abnormal return earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies, over the period May 1994-Dec 2015. Portfolio 1 contains companies with the most favourable consensus recommendations. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section *4. Method*. For each dataset, we run three time-series regressions, applying the CAPM, Fama-French ("FF") three factor model, and the Carhart ("FFC") four-factor model. The CAPM estimates in columns (1, 4, 7 and 10) are calculated from a time-series regression of the monthly portfolio 1 excess return on the market excess return. The Fama-French three factor model estimates in columns (2, 5, 8 and 11) are calculated by adding the return of a zero-investment size portfolio ("SMB") and that of a zero-investment book-to-market portfolio ("HML") as independent variables. Finally, the Carhart four-factor model estimates in columns (3, 6, 9 and 12) are calculated by adding the return of a zero-investment price momentum portfolio ("MOM") as an independent variable. We also introduce a dummy variable, which is set to one in the period before Regulation Fair Disclosure (May 1994-Oct 2000) and zero afterwards (Nov 2000-Dec 2015). Furthermore, interaction terms are added. These represent the dummy multiplied with each of the factor returns in the three asset-pricing models. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French's data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

	Ordinary			JBold subset			BBold subset			Changes subset		
	CAPM	**FF**	**FFC**	**CAPM**	**FF**	**FFC**	**CAPM**	**FF**	**FFC**	**CAPM**	**FF**	**FFC**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Rm - Rf	0.906***	0.951***	0.990***	0.940***	0.982***	1.004***	0.907***	0.971***	1.011***	0.923***	0.969***	1.000***
	(0.035)	(0.030)	(0.032)	(0.032)	(0.028)	(0.031)	(0.033)	(0.030)	(0.036)	(0.034)	(0.031)	(0.035)
SMB		-0.267***	-0.263***		-0.238***	-0.236***		-0.322***	-0.318***		-0.253***	-0.250***
		(0.044)	(0.044)		(0.038)	(0.037)		(0.055)	(0.049)		(0.041)	(0.040)
HML		-0.200***	-0.204***		-0.121**	-0.123**		-0.001	-0.005		-0.097	-0.100
		(0.051)	(0.053)		(0.050)	(0.052)		(0.059)	(0.057)		(0.059)	(0.062)
MOM			0.075**			0.039			0.076**			0.057*
			(0.034)			(0.028)			(0.031)			(0.032)
Pre-Reg FD	0.498*	0.345	0.331	0.416*	0.285	0.244	0.470	0.218	0.526**	0.579**	0.436**	0.490**
	(0.259)	(0.219)	(0.230)	(0.244)	(0.201)	(0.204)	(0.323)	(0.269)	(0.262)	(0.241)	(0.200)	(0.206)
[Rm - Rf] * Pre-Reg FD	0.209***	0.095	0.061	0.094	0.007	-0.006	-0.089	-0.029	-0.107	0.114**	0.036	0.001
	(0.066)	(0.066)	(0.069)	(0.064)	(0.061)	(0.063)	(0.081)	(0.077)	(0.074)	(0.056)	(0.055)	(0.059)
SMB * Pre-Reg FD		-0.000	-0.007		0.009	0.003		0.107	0.120*		0.006	0.005
		(0.078)	(0.079)		(0.077)	(0.077)		(0.078)	(0.070)		(0.071)	(0.070)
HML * Pre-Reg FD		-0.031	-0.002		-0.048	-0.013		0.175	0.016		-0.052	-0.068
		(0.115)	(0.137)		(0.104)	(0.114)		(0.115)	(0.124)		(0.109)	(0.128)
MOM * Pre-Reg FD			-0.042			0.003			-0.283***			-0.081
			(0.072)			(0.065)			(0.068)			(0.069)
Constant	-0.109	0.019	-0.011	-0.060	0.036	0.020	0.071	0.152	0.122	-0.102	-0.009	-0.031
	(0.120)	(0.103)	(0.103)	(0.105)	(0.089)	(0.090)	(0.115)	(0.097)	(0.099)	(0.114)	(0.100)	(0.101)
Observations	260	260	260	260	260	260	260	260	260	260	260	260
R-squared	0.860	0.895	0.899	0.894	0.919	0.920	0.818	0.875	0.888	0.875	0.902	0.905

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To test our third hypothesis[18], we run a Fama-French-Carhart four-factor regression with a dummy variable that separates the two periods (see **Table 4**). Furthermore, we add interaction terms of the dummy with the factors. Since we assign a value of one to the dummy variable for the pre-Regulation Fair Disclosure period, the alpha and coefficients without interaction terms correspond to the values after Regulation Fair Disclosure. Indeed, these values match those of **Appendix Table II** Panel A, which reports the regressions for the post-regulation period. The interaction terms can be interpreted as the difference between the two periods, i.e. by adding the interaction term coefficients to the corresponding coefficients without interaction terms, one gets the coefficients pre-Regulation Fair Disclosure. Most importantly for our third hypothesis, the dummy variable itself describes the difference in alpha between the two periods. Therefore, given that the third hypothesis is true, we expect that the interaction term will be positive and statistically significant.

Looking at **Table 4**, we find that the interaction term is economically significant for each of the four buy portfolios (ranging from 3% for the Jegadeesh and Kim subset to 6.5% for the Bagnoli et al. subset). Furthermore, the interaction term is statistically significant at the 5% level when looking at the Bagnoli et al. and Changes buy portfolios

5.3 Potential issues and robustness tests

5.3.1 Investment delay

In order to test the validity of our findings, we conduct three robustness tests. The first of these is found in **Appendix Table IV**, which shows the effect that an investment delay of one, three, or five trading days has on our alphas. These delays reflect that investors might not be able to immediately access or trade on new recommendations. The results in **Appendix Table IV** can be compared to those in **Table 3**, which has no investment delay. It is important to note that the gross and net alphas are affected more or less equally by the investment delay, since the effect on annual turnover is only marginal.

Looking at the statistically significant (10% or lower) Fama-French-Carhart alphas from **Table 3**, we find the following. First of all, we notice that the pre-regulation alpha of the Changes

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[18] Hypothesis 3: Given that Regulation Fair Disclosure was effective, we hypothesize that the abnormal return of our portfolios should decrease after it came into effect. We expect that this effect will be particularly pronounced for our portfolios based on bold recommendations.

portfolio decreases in both magnitude and statistical significance as we increase the investment delay. Indeed, while the gross alpha is statistically significant at the 5% level without any investment delay, the significance level reduces to 10% with three days delay, and the alpha becomes statistically insignificant at any reasonable level with five days delay. The decrease in alpha is likely explained by the finding of Stickel (1995) that a large part of the abnormal return of recommendation changes is found within the first few days after issuance.

Second, we find similar results for BBold when looking at the whole time period, and we believe that the explanation is the same as above. Looking at the pre-regulation period, however, we find that the BBold alphas are generally quite similar both in magnitude and significance level, despite investment delays. In fact, the alpha becomes even more economically and statistically significant with three and five days delay, compared to the base case of no delay.

We believe that this consistency in alphas during the pre-regulation period is explained by the studies of Shane et al. (2001) and Jaggi et al. (2009), whose findings suggest that the private information available before Reg. FD was of a more long-term nature. Given that BBold captures recommendations based on more private information (in line with Clement and Tse's (2005) finding that "bold [non-herding] forecasts appear to reflect analysts' relevant private information to a greater extent than herding forecasts") and that *long-term* private information was more readily available before Regulation Fair Disclosure, it makes sense that the alphas for BBold are less affected by *short-term* investment delays.

5.3.2 Portfolio rebalancing frequency

As a second robustness test, we check the effect that a reduced rebalancing frequency (weekly, bi-weekly, or monthly, instead of daily) has on our findings (see **Appendix Table V**). Looking at the gross Fama-French-Carhart alphas of **Appendix Table V** and comparing them to the statistically significant (10% or lower) alphas from **Table 3**, we find that the alpha of BBold decreases and no longer is statistically significant when looking at the whole period.

Moreover, the gross alpha of Changes in the pre-regulation period is reduced, but it is still statistically significant at the same level as before (5%) with weekly rebalancing, although this significance level increases to 10% with bi-weekly balancing, and to more than 10% with monthly rebalancing.

Finally, we find that the gross alpha of BBold is quite consistent across rebalancing periods, and it is statistically significant at a 1% (5%) level with weekly and monthly (bi-weekly) rebalancing. We believe that the explanation for this consistency is the same as the one we provided for investment delays, i.e. that BBold captured recommendations based on long-term private information before Regulation Fair Disclosure, and therefore the onset of any returns associated with its recommendations might be delayed (long-term) as well. Noticeably, the alpha is even higher with monthly rebalancing than with daily rebalancing, but this finding should be taken with some caution as the relatively few rebalancing dates with monthly rebalancing makes the alpha more sensitive to these particular dates, and hence its relatively high alpha could be due to chance.

Most importantly, we find that the reduced turnover associated with weekly, bi-weekly, and monthly rebalancing leads to alphas net of transaction costs that are statistically significant at the 10% level. Moreover, these net alphas are all economically significant, with the lowest one being about 5.5% on an annual level.

5.3.3 Business cycle impact

We observe that the post-regulation period includes two recessions, as defined by NBER, whereas the pre-regulation period has none. This could potentially bias our results with regard to our second and third hypotheses. For both of these hypotheses, the strong results in the pre-regulation period (relative to the results in the post-regulation period) could possibly be explained by the lack of any recessions during that particular period. To test this, we incorporate a dummy variable based on US business cycle expansion and contractions, as reported by NBER. This dummy is set to one for months defined as recessions.

Appendix Table VI shows the post-regulation regressions after we have added the recession dummy. Most importantly, the dummy variable is not statistically significant at any reasonable level across asset-pricing models and datasets. Moreover, the coefficient on the dummy variable is small in magnitude for both the BBold and Changes subsets, when looking at the Fama-French-Carhart regressions, which are the two subsets for which we have found support for hypotheses two and three.

In conclusion, the lack of recessions during pre-regulation period does not appear to bias our earlier findings with regard to hypotheses two or three.

6. Conclusions and implications

This thesis has aimed to introduce a trading strategy based on a consensus restricted to non-herding ("bold") recommendations, and to evaluate its performance against a non-restricted ("ordinary") consensus. We find that bold recommendations were, indeed, more profitable prior to Regulation Fair Disclosure, which became effective in October, 2000. However, we do not find statistically significant results in the subsequent period. This is in line with prior studies showing that the regulation effectively limited analysts' access to private information (Kadan et al. (2009)), which is often associated with boldness (Clement and Tse (2005)). To our surprise, the seemingly less sophisticated approach of restricting the consensus to recommendation changes yielded not too distant results.

We reach our findings by constructing a portfolio that purchases S&P 100 companies with the most favourable consensus recommendations. We then run regressions, controlling for the Fama-French-Carhart four-factors. Unless stated otherwise, the results refer to recommendations, issued by sell-side analysts, over the time period May 1994-Dec 2015.

We do (not) find economically significant positive annual abnormal returns gross (net) of transaction costs, but – contrary to what we expected – none of these alphas are statistically significant at any reasonable level. In other words, we do not find support for our first hypothesis. However, this apparent lack of support might simply reflect characteristics of our sample. Indeed, Stickel (1995) found that "smaller companies have larger reactions to recommendations than do larger firms, which is consistent with the existence of fewer alternative information sources about the value of smaller companies".

Next, recommendations are classified as bold using two different definitions. The simpler version defines bold recommendations as those deviating from last day's consensus by at least one level (Bagnoli et al. (2010)), whereas the more complex one captures recommendations that are more bold, relative to the consensus, than the analyst's most recent recommendation for the same company (Jegadeesh and Kim (2010)). Finally, we also consider upgrades and downgrades, due to the prominence of such recommendations in previous literature.

The findings with regard to our second hypothesis are less clear-cut. Looking at the entire time period, we find that the annual alpha generated by restricting the strategy to only consider bold recommendations, as defined by Bagnoli et al., is about twice as large (around 2.2%) as the alpha based on all of our other datasets (all recommendations, Jegadeesh and Kim's definition of bold, and changes). Although the alpha is economically significant, the alpha is only statistically significant at the 10% level, while the others are in fact not significantly different from zero at all.

Looking at the pre-regulation period in isolation, however, we find that a buy portfolio based on a consensus restricted to Bagnoli et al.'s bold (all) recommendations generates a gross annual alpha of 7.8% (3.8%) that is (not) statistically significant at the 5% level. For comparison, a portfolio restricted by our second bold definition (restricted to changes) has a gross annual alpha of 3.2% (5.5%) that is statistically insignificant at any reasonable level (statistically significant at the 5% level).

We believe that the poor performance of the Jegadeesh and Kim bold definition relative to the Bagnoli et al. one and its failure to outperform the ordinary consensus may be explained by the inability to capture recommendations of analysts who are consistently bold.

Notably, we find that both the Bagnoli et al. and Changes portfolios have positive and economically significant alphas net of transaction costs (4.5% and 1.8%, respectively) for the pre-regulation period. By comparison, Barber et al. did not find any positive alphas net of transaction costs. Moreover, we identify in our robustness test of rebalancing frequencies that there is a positive trade-off between lower transaction costs and information available in the consensus. As a result, the net abnormal return increases as we decrease the rebalancing frequency.

We believe that the above is explained by the findings of previous studies (Shane et al. (2001) and Jaggi et al. (2009)), which suggest that the private information available before Regulation Fair Disclosure was long-term in nature. Consequently, it makes sense that recommendations reflecting long-term private information, which boldness is associated with, should generate more *long-term* positive returns. Thus, the sensitivity to less frequent rebalancing is expected to be low, as the potential loss of *short-term* returns is outweighed by reduced trading costs.

In support of our third hypothesis, we find economically significant decreases in the gross alphas following Regulation Fair Disclosure for all subsets, and statistically significant decreases for the Bagnoli et al. and Changes subsets. Generally, these results support earlier findings (e.g.

Zitzewitz (2002) and Gintschel and Markov (2004)) that Regulation Fair Disclosure was effective in reducing analyst access to private information.

All our main findings are robust to investment delays and less frequent rebalancing. Moreover, we do not find a potential bias from the presence of recessions in the post-regulation period.

Finally, we have two suggestions for future research. First of all, we encourage future studies to test whether our findings are robust to the choice of database, given the observation of Ljungqvist et al. (2009) that I/B/E/S contains "[…] alterations made as a result of brokers' requests for retrospective changes to their buy/hold/sell recommendation scales" (see discussion in section *3.1.3 Data issues* for further details). Second, it would be interesting to apply our strategy to a larger sample of companies, including smaller companies. Given the finding of Stickel (1995) that small companies have larger stock reactions to recommendation changes, we believe that the results from such a sample could be even more pronounced than those we find.

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Appendix

Table I. Percentage Annual Abnormal Returns of an Equal-weighted Portfolio 1 per Dataset and Period

This table shows the annual abnormal return earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies, over the period May 1994-Dec 2015. Portfolio 1 contains companies with the most favourable consensus recommendations. Unlike in Table 3, the values reported in this table assume equal-weighting of companies within each portfolio. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section *4. Method*. The percentage raw returns in column (1) are calculated as the geometric mean annual return earned by portfolio 1 for each subset and period. The annualized CAPM alpha (i.e. intercept) in column (2) is estimated from a time-series regression of the monthly portfolio 1 excess return on the market excess return, which is then multiplied by 12 to derive an annualized alpha. The annualized Fama-French ("FF") three factor model alpha (i.e. intercept) in column (3) is estimated by adding the return of a zero-investment size portfolio ("SMB") and that of a zero-investment book-to-market portfolio ("HML") as independent variables. The annualized Carhart ("FFC") four-factor model alpha (i.e. intercept) in column (4) is estimated by adding the return of a zero-investment price momentum portfolio ("MOM") as an independent variable. Annual turnover in column (5) is calculated as the average percentage of the portfolio's holdings that have been sold from one trading day to another, multiplied by the number of trading days per year (approximately 250). The net annual return, found in columns (6-8), is then calculated by subtracting the annual turnover multiplied by the round-trip cost of a trade from the corresponding alphas in columns (2-4). The round-trip cost is set to 0.57 percent, in accordance with Keim and Madhavan's (1998) estimate for the largest companies by market capitalization. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French's data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	Annualized alpha from FF (3)	Annualized alpha from FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	Net annual return from FF (7)	Net annual return from FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	11.516	2.496*	2.340*	2.256	749	-1.771	-1.927	-2.011
JBold subset	12.606	3.276**	2.796**	3.480***	619	-0.254	-0.734	-0.050
BBold subset	13.020	3.804**	3.144**	4.044***	546	0.693	0.033	0.933
Changes subset	12.212	3.096**	2.676**	2.856**	649	-0.604	-1.024	-0.844
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	24.249	4.296	2.256	6.276**	710	0.250	-1.790	2.230
JBold subset	24.780	5.640	3.384	7.812***	606	2.186	-0.070	4.358
BBold subset	24.099	6.060	2.988	9.264***	572	2.799	-0.273	6.003**
Changes subset	24.810	5.400	2.868	7.752***	634	1.788	-0.744	4.140
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	6.467	1.788	2.100	1.692	772	-2.611*	-2.299*	-2.707*
JBold subset	7.759	2.808**	2.688***	2.712**	631	-0.790	-0.910	-0.886
BBold subset	8.580	3.600***	3.564***	3.552***	540	0.519	0.483	0.471
Changes subset	7.210	2.412*	2.484**	2.160*	662	-1.363	-1.291	-1.615

Significance levels are based on monthly returns and their corresponding robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Table II. Percentage Abnormal Monthly Returns of Portfolio 1 per Dataset and Period

This table shows the monthly abnormal return earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies, over the period May 1994-Dec 2015. Portfolio 1 contains companies with the most favourable consensus recommendations. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section *4. Method*. For each dataset, we run three time-series regressions, applying the CAPM, Fama-French ("FF") three factor model, and the Carhart ("FFC") four-factor model. The CAPM estimates in columns (1, 4, 7 and 10) are calculated from a time-series regression of the monthly portfolio 1 excess return on the market excess return. The Fama-French three factor model estimates in columns (2, 5, 8 and 11) are calculated by adding the return of a zero-investment size portfolio ("SMB") and that of a zero-investment book-to-market portfolio ("HML") as independent variables. Finally, the Carhart four-factor model estimates in columns (3, 6, 9 and 12) are calculated by adding the return of a zero-investment price momentum portfolio ("MOM") as an independent variable. **Panel A.** shows the estimates for the entire time period of our sample, May 1994-Dec 2015, **Panel B.** for the pre-Regulation Fair Disclosure period, May 1994-Oct 2000, and **Panel C.** for the post-regulation period, Nov 2000-Dec 2015. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French's data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

Panel A. All periods, May 1994-Dec 2015

	Ordinary			JBold subset			BBold subset			Changes subset		
	CAPM	FF	FFC	CAPM	FF	FFC	CAPM	FF	FFC	CAPM	FF	FFC
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Rm - Rf	0.969***	0.980***	1.011***	0.970***	0.989***	1.006***	0.886***	0.948***	0.953***	0.960***	0.985***	1.006***
	(0.030)	(0.027)	(0.026)	(0.028)	(0.025)	(0.025)	(0.030)	(0.026)	(0.030)	(0.028)	(0.025)	(0.025)
SMB		-0.275***	-0.285***		-0.230***	-0.236***		-0.296***	-0.298***		-0.250***	-0.257***
		(0.036)	(0.036)		(0.035)	(0.033)		(0.034)	(0.036)		(0.032)	(0.031)
HML		-0.237***	-0.209***		-0.145***	-0.129***		0.045	0.049		-0.130***	-0.111***
		(0.045)	(0.042)		(0.039)	(0.038)		(0.042)	(0.044)		(0.045)	(0.042)
MOM			0.076***			0.044**			0.011			0.052**
			(0.028)			(0.022)			(0.036)			(0.025)
Constant	0.078	0.147	0.087	0.080	0.125	0.089	0.192	0.192*	0.183*	0.091	0.133	0.091
	(0.110)	(0.094)	(0.095)	(0.097)	(0.083)	(0.083)	(0.118)	(0.099)	(0.108)	(0.103)	(0.090)	(0.091)
Observations	260	260	260	260	260	260	260	260	260	260	260	260
R-squared	0.847	0.891	0.897	0.890	0.918	0.920	0.815	0.871	0.872	0.868	0.899	0.902

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B. Pre-Reg FD, May 1994-Oct 2000

	Ordinary			JBold subset			BBold subset			Changes subset		
	CAPM	**FF**	**FFC**	**CAPM**	**FF**	**FFC**	**CAPM**	**FF**	**FFC**	**CAPM**	**FF**	**FFC**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Rm - Rf	1.115***	1.046***	1.052***	1.034***	0.990***	0.997***	0.818***	0.941***	0.904***	1.037***	1.005***	1.001***
	(0.057)	(0.060)	(0.062)	(0.056)	(0.055)	(0.055)	(0.074)	(0.072)	(0.065)	(0.045)	(0.047)	(0.049)
SMB		-0.267***	-0.269***		-0.230***	-0.233***		-0.214***	-0.198***		-0.247***	-0.245***
		(0.066)	(0.066)		(0.067)	(0.068)		(0.056)	(0.051)		(0.058)	(0.058)
HML		-0.232**	-0.206		-0.169*	-0.135		0.174*	0.011		-0.149	-0.168
		(0.104)	(0.128)		(0.093)	(0.102)		(0.099)	(0.112)		(0.092)	(0.113)
MOM			0.032			0.042			-0.207***			-0.024
			(0.064)			(0.060)			(0.061)			(0.061)
Constant	0.389*	0.363*	0.320	0.355	0.321*	0.264	0.542*	0.370	0.648**	0.478**	0.427**	0.459**
	(0.231)	(0.195)	(0.209)	(0.221)	(0.182)	(0.186)	(0.304)	(0.253)	(0.246)	(0.214)	(0.175)	(0.183)
Observations	78	78	78	78	78	78	78	78	78	78	78	78
R-squared	0.851	0.883	0.883	0.868	0.897	0.898	0.662	0.784	0.812	0.857	0.893	0.893

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel C. Post-Reg FD, Nov 2000-Dec 2015

	Ordinary			JBold subset			BBold subset			Changes subset		
	CAPM	FF	FFC	CAPM	FF	FFC	CAPM	FF	FFC	CAPM	FF	FFC
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rm - Rf	0.906***	0.951***	0.990***	0.940***	0.982***	1.004***	0.907***	0.971***	1.011***	0.923***	0.969***	1.000***
	(0.035)	(0.030)	(0.032)	(0.032)	(0.028)	(0.031)	(0.033)	(0.030)	(0.036)	(0.034)	(0.031)	(0.034)
SMB		-0.267***	-0.263***		-0.238***	-0.236***		-0.322***	-0.318***		-0.253***	-0.250***
		(0.043)	(0.044)		(0.038)	(0.037)		(0.055)	(0.049)		(0.041)	(0.040)
HML		-0.200***	-0.204***		-0.121**	-0.123**		-0.001	-0.005		-0.097	-0.100
		(0.051)	(0.053)		(0.050)	(0.052)		(0.058)	(0.057)		(0.059)	(0.062)
MOM			0.075**			0.039			0.076**			0.057*
			(0.034)			(0.027)			(0.031)			(0.032)
Constant	-0.109	0.019	-0.011	-0.060	0.036	0.020	0.071	0.152	0.122	-0.102	-0.009	-0.031
	(0.119)	(0.102)	(0.102)	(0.104)	(0.088)	(0.089)	(0.115)	(0.096)	(0.098)	(0.114)	(0.100)	(0.100)
Observations	182	182	182	182	182	182	182	182	182	182	182	182
R-squared	0.859	0.898	0.905	0.904	0.927	0.929	0.877	0.910	0.917	0.880	0.904	0.908

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table III. Percentage Annual Abnormal Returns of Portfolios 2 and 3 per Dataset and Period

This table shows the annual abnormal return earned by portfolios 2 and 3, formed on the basis of consensus analyst recommendations for S&P 100 companies, over the period May 1994-Dec 2015. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section 4. Method. The percentage raw returns in column (1) are calculated as the geometric mean annual return earned by portfolio 1 for each subset and period. The annualized CAPM alpha (i.e. intercept) in column (2) is estimated from a time-series regression of the monthly portfolio 1 excess return on the market excess return, which is then multiplied by 12 to derive an annualized alpha. The annualized Fama-French ("FF") three factor model alpha (i.e. intercept) in column (3) is estimated by adding the return of a zero-investment size portfolio ("SMB") and that of a zero-investment book-to-market portfolio ("HML") as independent variables. The annualized Carhart ("FFC") four-factor model alpha (i.e. intercept) in column (4) is estimated by adding the return of a zero-investment price momentum portfolio ("MOM") as an independent variable. Annual turnover in column (5) is calculated as the average percentage of the portfolio's holdings that have been sold from one trading day to another, multiplied by the number of trading days per year (approximately 250). The net annual return, found in columns (6-8), is then calculated by subtracting the annual turnover multiplied by the round-trip cost of a trade from the corresponding alphas in columns (2-4). The round-trip cost is set to 0.57 percent, in accordance with Keim and Madhavan's (1998) estimate for the largest companies by market capitalization. **Panel A.** shows the estimates for portfolio 2, i.e. the hold portfolio. **Panel B.** shows the estimates for portfolio 3, i.e. the sell portfolio. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French's data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

Panel A. Portfolio 2 – Hold

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	9.455	1.020	1.092	1.548	1035	-4.878***	-4.806***	-4.350***
JBold subset	6.626	-1.788	-1.824	-0.684	1484	-10.249***	-10.285***	-9.145***
BBold subset	11.985	3.000	3.468	4.824	1743	-6.934**	-6.466**	-5.110*
Changes subset	9.251	0.408	0.996	1.488	1213	-6.509***	-5.921***	-5.429***
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	20.358	3.060	1.308	2.652	1200	-3.782	-5.534	-4.190
JBold subset	12.933	-5.040	-6.300	-2.832	1492	-13.543***	-14.803***	-11.335***
BBold subset	30.163	7.716	7.356	9.720	1818	-2.648	-3.008	-0.644
Changes subset	18.215	-1.116	-2.520	-2.976	1312	-8.595***	-9.999***	-10.455***
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	5.090	0.552	1.488	1.560	970	-4.976***	-4.040***	-3.968***
JBold subset	4.033	-0.336	0.048	0.540	1487	-8.811***	-8.427***	-7.935***
BBold subset	4.994	0.672	1.128	2.052	1714	-9.101***	-8.645***	-7.721***
Changes subset	5.621	1.020	2.616*	2.796*	1177	-5.691***	-4.095***	-3.915**

Significance levels are based on monthly returns and their corresponding robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Panel B. Portfolio 3 – Sell

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	6.958	-1.080	-1.800	0.204	888	-6.144***	-6.864***	-4.860***
JBold subset	7.079	-1.500	-1.560	-0.132	814	-6.138***	-6.198***	-4.770***
BBold subset	6.866	-2.184	-1.752	-1.020	641	-5.835***	-5.403***	-4.671***
Changes subset	7.605	-0.804	-1.212	0.108	770	-5.195***	-5.603***	-4.283**
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	18.726	4.332	0.036	6.144	1137	-2.146	-6.442	-0.334
JBold subset	17.623	0.084	-2.652	2.544	929	-5.214	-7.950*	-2.754
BBold subset	21.913	0.984	0.564	-1.908	627	-2.590	-3.010	-5.482**
Changes subset	18.879	2.328	0.792	6.120	987	-3.298	-4.834	0.494
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	2.278	-2.184	-1.716	-1.032	788	-6.676***	-6.208***	-5.524***
JBold subset	2.855	-1.716	-0.732	-0.204	770	-6.106***	-5.122***	-4.594***
BBold subset	0.999	-3.552**	-2.544	-1.872	653	-7.274***	-6.266***	-5.594***
Changes subset	3.106	-1.404	-1.320	-0.804	683	-5.300***	-5.216***	-4.700***

Significance levels are based on monthly returns and their corresponding robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Table IV. The Effect of Investment Delays on the Annual Abnormal Returns of Portfolio 1 per Dataset and Period

This table shows the annual abnormal return earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies, over the period May 1994-Dec 2015. Portfolio 1 contains companies with the most favourable consensus recommendations. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section 4. Method. The percentage raw returns in column (1) are calculated as the geometric mean annual return earned by portfolio 1 for each subset and period. The annualized CAPM alpha (i.e. intercept) in column (2) is estimated from a time-series regression of the monthly portfolio 1 excess return on the market excess return, which is then multiplied by 12 to derive an annualized alpha. The annualized Fama-French ("FF") three factor model alpha (i.e. intercept) in column (3) is estimated by adding the return of a zero-investment size portfolio ("SMB") and that of a zero-investment book-to-market portfolio ("HML") as independent variables. The annualized Carhart ("FFC") four-factor model alpha (i.e. intercept) in column (4) is estimated by adding the return of a zero-investment price momentum portfolio ("MOM") as an independent variable. Annual turnover in column (5) is calculated as the average percentage of the portfolio's holdings that have been sold from one trading day to another, multiplied by the number of trading days per year (approximately 250). The net annual return, found in columns (6-8), is then calculated by subtracting the annual turnover multiplied by the round-trip cost of a trade from the corresponding alphas in columns (2-4). The round-trip cost is set to 0.57 percent, in accordance with Keim and Madhavan's (1998) estimate for the largest companies by market capitalization. **Panel A.** shows the estimates when Portfolio 1 is constructed based on a one day investment delay, **Panel B.** on three days investment delay, and **Panel C.** on five days investment delay. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French's data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

Panel A. One day investment delay

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	9.055	0.132	0.972	0.216	687	-3.783***	-2.943***	-3.699***
JBold subset	8.979	0.012	0.504	0.060	581	-3.302***	-2.810***	-3.254***
BBold subset	10.526	1.908	1.944	1.956	506	-0.977	-0.941	-0.929
Changes subset	9.150	0.228	0.732	0.132	601	-3.196***	-2.692**	-3.292***
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	27.582	4.752*	4.500*	3.756	638	1.116	0.864	0.120
JBold subset	25.293	3.840	3.504	3.156	585	0.504	0.168	-0.180
BBold subset	24.405	6.036*	3.984	7.404**	575	2.761	0.709	4.129
Changes subset	26.904	4.884*	4.260**	4.404**	642	1.222	0.598	0.742
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	1.962	-2.436*	-0.912	-1.272	715	-6.509***	-4.985***	-5.345***
JBold subset	2.655	-1.872	-0.804	-1.008	586	-5.213***	-4.145***	-4.349***
BBold subset	5.063	0.516	1.500	1.188	483	-2.237*	-1.253	-1.565
Changes subset	2.323	-2.136	-1.020	-1.332	589	-5.495***	-4.379***	-4.691***

Significance levels are based on monthly returns and their corresponding robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Panel B. Three days investment delay

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	8.910	-0.072	0.708	-0.048	687	-3.986***	-3.206***	-3.962***
JBold subset	9.249	0.252	0.720	0.348	581	-3.060***	-2.592***	-2.964***
BBold subset	10.376	1.764	1.764	1.860	506	-1.121	-1.121	-1.025
Changes subset	9.063	0.180	0.672	0.108	601	-3.246***	-2.754**	-3.318***
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	27.164	4.164	3.876	3.324	639	0.519	0.231	-0.321
JBold subset	26.794	5.256**	4.836**	4.164*	583	1.932	1.512	0.840
BBold subset	25.807	7.296*	4.992	8.832***	573	4.030	1.726	5.566*
Changes subset	27.124	5.208**	4.524**	4.176*	642	1.548	0.864	0.516
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	1.913	-2.520*	-1.092	-1.428	713	-6.586***	-5.158***	-5.494***
JBold subset	2.493	-2.052*	-1.020	-1.164	587	-5.396***	-4.364***	-4.508***
BBold subset	4.356	-0.168	0.816	0.528	484	-2.924**	-1.940	-2.228*
Changes subset	2.131	-2.304*	-1.176	-1.452	590	-5.666***	-4.538***	-4.814***

Significance levels are based on monthly returns and their corresponding robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Panel C. Five days investment delay

	Geometric mean annual raw return	Annualized alpha from			Annual turnover	Net annual return from		
		CAPM	FF	FFC		CAPM	FF	FFC
Portfolio 1 per period and dataset	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All periods (May 1994-Dec 2015)								
Ordinary	7.984	-0.900	-0.120	-0.936	687	-4.813***	-4.033***	-4.849***
JBold subset	8.665	-0.264	0.216	-0.084	581	-3.578***	-3.098***	-3.398***
BBold subset	9.975	1.356	1.392	1.404	507	-1.535	-1.499	-1.487
Changes subset	8.626	-0.252	0.264	-0.264	602	-3.683***	-3.167***	-3.695***
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	25.735	2.976	2.640	1.908	638	-0.659	-0.995	-1.727
JBold subset	24.949	3.900	3.516*	2.892	582	0.581	0.197	-0.427
BBold subset	25.490	6.840*	4.800	7.944***	576	3.559	1.519	4.663
Changes subset	25.502	3.900	3.372*	2.844	642	0.242	-0.286	-0.814
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	1.166	-3.228**	-1.812	-2.184	714	-7.298***	-5.882***	-6.254***
JBold subset	2.353	-2.184*	-1.128	-1.260	587	-5.532***	-4.476***	-4.608***
BBold subset	3.928	-0.588	0.444	0.168	484	-3.348**	-2.316*	-2.592**
Changes subset	2.107	-2.340	-1.164	-1.404	591	-5.709***	-4.533***	-4.773***

Significance levels are based on monthly returns and their corresponding robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Table V. The Effect of Less Frequent Rebalancing on the Annual Abnormal Returns of Portfolio 1 per Dataset and Period

This table shows the annual abnormal return earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies, over the period May 1994-Dec 2015. Portfolio 1 contains companies with the most favourable consensus recommendations. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section 4. Method. The percentage raw returns in column (1) are calculated as the geometric mean annual return earned by portfolio 1 for each subset and period. The annualized CAPM alpha (i.e. intercept) in column (2) is estimated from a time-series regression of the monthly portfolio 1 excess return on the market excess return, which is then multiplied by 12 to derive an annualized alpha. The annualized Fama-French (“FF”) three factor model alpha (i.e. intercept) in column (3) is estimated by adding the return of a zero-investment size portfolio (”SMB”) and that of a zero-investment book-to-market portfolio (”HML”) as independent variables. The annualized Carhart (“FFC”) four-factor model alpha (i.e. intercept) in column (4) is estimated by adding the return of a zero-investment price momentum portfolio (”MOM”) as an independent variable. Annual turnover in column (5) is calculated as the average percentage of the portfolio’s holdings that have been sold from one trading day to another, multiplied by the number of trading days per year (approximately 250). The net annual return, found in columns (6-8), is then calculated by subtracting the annual turnover multiplied by the round-trip cost of a trade from the corresponding alphas in columns (2-4). The round-trip cost is set to 0.57 percent, in accordance with Keim and Madhavan’s (1998) estimate for the largest companies by market capitalization. **Panel A.** shows the estimates when portfolio 1 is rebalanced on a weekly level, **Panel B.** on a bi-weekly level, and **Panel C.** on a monthly (four weeks) level. The portfolios are rebalanced on Mondays, provided it is a trading day. Otherwise, rebalancing occurs on the next trading day. For simplicity, we assume that a stock is sold immediately if it is removed from the S&P 100 index. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French’s data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

Panel A. Weekly rebalancing

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	9.283	0.300	1.116	0.324	507	-2.590**	-1.774	-2.566**
JBold subset	9.340	0.348	0.852	0.396	437	-2.143*	-1.639*	-2.095**
BBold subset	10.161	1.548	1.572	1.536	398	-0.721	-0.697	-0.733
Changes subset	9.263	0.360	0.864	0.300	459	-2.256*	-1.752	-2.316**
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	27.827	4.716	4.440*	3.780	477	1.997	1.721	1.061
JBold subset	26.415	4.896*	4.488**	3.840	428	2.456	2.048	1.400
BBold subset	25.498	6.876*	4.644	7.848***	469	4.203	1.971	5.175*
Changes subset	27.533	5.616**	5.040**	4.680**	493	2.806	2.230	1.870
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	2.183	-2.244	-0.780	-1.152	526	-5.242***	-3.778***	-4.150***
JBold subset	2.748	-1.788	-0.660	-0.876	447	-4.336***	-3.208***	-3.424***
BBold subset	4.176	-0.348	0.708	0.372	374	-2.480*	-1.424	-1.760
Changes subset	2.257	-2.196	-1.104	-1.368	451	-4.767***	-3.675***	-3.939***

Significance levels are based on monthly returns and their corresponding robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Panel B. Bi-weekly rebalancing

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	8.879	-0.072	0.720	-0.072	418	-2.455*	-1.663	-2.455**
JBold subset	8.996	0.048	0.516	0.156	375	-2.090*	-1.622*	-1.982**
BBold subset	10.279	1.668	1.728	1.608	341	-0.276	-0.216	-0.336
Changes subset	9.227	0.288	0.816	0.300	390	-1.935	-1.407	-1.923*
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	26.835	3.876	3.576	2.784	385	1.682	1.382	0.590
JBold subset	24.890	3.708	3.360	2.940	365	1.628	1.280	0.860
BBold subset	25.631	6.720*	4.752	7.668**	400	4.440	2.472	5.388*
Changes subset	27.074	5.028**	4.392**	4.176*	408	2.702	2.066	1.850
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	1.984	-2.424*	-0.984	-1.344	438	-4.921***	-3.481***	-3.841***
JBold subset	2.819	-1.728	-0.696	-0.852	386	-3.928***	-2.896***	-3.052***
BBold subset	4.288	-0.204	0.792	0.468	322	-2.039	-1.043	-1.367
Changes subset	2.367	-2.088	-0.936	-1.188	388	-4.300***	-3.148**	-3.400***

Significance levels are based on monthly returns and their corresponding robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Panel C. Monthly rebalancing

Portfolio 1 per period and dataset	Geometric mean annual raw return (1)	Annualized alpha from CAPM (2)	FF (3)	FFC (4)	Annual turnover (5)	Net annual return from CAPM (6)	FF (7)	FFC (8)
All periods (May 1994-Dec 2015)								
Ordinary	8.435	-0.432	0.432	-0.588	322	-2.267	-1.403	-2.423**
JBold subset	9.231	0.228	0.720	0.408	304	-1.505	-1.013	-1.325
BBold subset	10.913	2.184	2.316*	2.208	293	0.514	0.646	0.538
Changes subset	7.963	-0.852	-0.276	-0.864	312	-2.630**	-2.054*	-2.642**
Pre-Reg FD (May 1994-Oct 2000)								
Ordinary	26.498	3.660	3.240	1.956	294	1.984	1.564	0.280
JBold subset	26.062	4.488*	4.092*	3.096	281	2.886	2.490	1.494
BBold subset	27.512	7.920**	5.988*	8.544***	338	5.993	4.061	6.617**
Changes subset	25.294	3.384	2.808	2.196	311	1.611	1.035	0.423
Post-Reg FD (Nov 2000-Dec 2015)								
Ordinary	1.506	-2.844*	-1.212	-1.728	340	-4.782***	-3.150**	-3.666***
JBold subset	2.724	-1.812	-0.792	-0.864	321	-3.642***	-2.622**	-2.694***
BBold subset	4.478	-0.036	1.044	0.768	280	-1.632	-0.552	-0.828
Changes subset	1.290	-3.108**	-1.884	-2.136*	319	-4.926***	-3.702***	-3.954***

Significance levels are based on monthly returns and their corresponding robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Table VI. The Effect of Business Cycles on the Annual Abnormal Returns of Portfolio 1 per Dataset

This table shows the monthly abnormal return earned by portfolio 1, formed on the basis of consensus analyst recommendations for S&P 100 companies, in the post-Regulation Fair Disclosure period (Nov 2000-Dec 2015). Portfolio 1 contains companies with the most favourable consensus recommendations. Recommendation data was gathered from I/B/E/S, stock price data from CRSP, and S&P 100 index constituents from Compustat. BBold and JBold refers to recommendations classified as bold using the definitions of Bagnoli et al. (2010) and Jegadeesh and Kim (2010), respectively. Changes refers to upgrades and downgrades. The subsets and portfolios are described in greater detail in section 4. Method. For each dataset, we run three time-series regressions, applying the CAPM, Fama-French (“FF”) three factor model, and the Carhart (“FFC”) four-factor model. The CAPM estimates in columns (1, 4, 7 and 10) are calculated from a time-series regression of the monthly portfolio 1 excess return on the market excess return. The Fama-French three factor model estimates in columns (2, 5, 8 and 11) are calculated by adding the return of a zero-investment size portfolio (”SMB”) and that of a zero-investment book-to-market portfolio (”HML”) as independent variables. Finally, the Carhart four-factor model estimates in columns (3, 6, 9 and 12) are calculated by adding the return of a zero-investment price momentum portfolio (”MOM”) as an independent variable. For each of the regressions, we add a dummy variable which equals one in months defined as recessions by NBER and zero otherwise. The datasets tested against the three models are described in section *4. Method*. Each t-statistic refers to the null hypothesis that the estimate is zero. Monthly returns for the three Fama-French factors and momentum as well as the risk-free rate were downloaded from Kenneth R. French’s data library. Each t-statistic refers to the null hypothesis that the return is zero. All values are in percent.

	Ordinary			JBold subset			BBold subset			Changes subset		
	CAPM	**FF**	**FFC**	**CAPM**	**FF**	**FFC**	**CAPM**	**FF**	**FFC**	**CAPM**	**FF**	**FFC**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Rm - Rf	0.903***	0.951***	0.996***	0.931***	0.975***	0.996***	0.898***	0.967***	1.012***	0.915***	0.964***	0.998***
	(0.039)	(0.034)	(0.035)	(0.034)	(0.030)	(0.033)	(0.034)	(0.032)	(0.039)	(0.036)	(0.033)	(0.037)
SMB		-0.267***	-0.267***		-0.231***	-0.231***		-0.318***	-0.318***		-0.248***	-0.248***
		(0.042)	(0.044)		(0.038)	(0.037)		(0.056)	(0.050)		(0.040)	(0.040)
HML		-0.200***	-0.203***		-0.123**	-0.124**		-0.002	-0.005		-0.098*	-0.100
		(0.051)	(0.053)		(0.049)	(0.051)		(0.058)	(0.057)		(0.059)	(0.061)
MOM			0.077**			0.036			0.076**			0.057*
			(0.035)			(0.027)			(0.033)			(0.032)
NBER Dummy	-0.174	0.008	0.203	-0.531	-0.349	-0.257	-0.507	-0.176	0.018	-0.425	-0.213	-0.069
	(0.520)	(0.413)	(0.336)	(0.384)	(0.336)	(0.306)	(0.360)	(0.333)	(0.318)	(0.463)	(0.413)	(0.360)
Constant	-0.083	0.018	-0.041	0.019	0.087	0.059	0.147	0.178*	0.119	-0.038	0.022	-0.021
	(0.119)	(0.109)	(0.110)	(0.112)	(0.095)	(0.097)	(0.124)	(0.107)	(0.114)	(0.118)	(0.104)	(0.108)
Observations	182	182	182	182	182	182	182	182	182	182	182	182
R-squared	0.859	0.898	0.905	0.905	0.927	0.929	0.879	0.910	0.917	0.881	0.904	0.908

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1