Analysts' stickiness, over-reaction and drift

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Abstract

We show that investor underreaction and overreaction to company news (Michaely, Thaler, and Womack, 1995; De Bondt and Thaler, 1985) can be traced back to sell-side analysts' tendency to delay their stock recommendations for several months. Analysts exhibit stickiness in their stock recommendations because they face reputational concern in changing such recommendations too often and/or difficulties in processing new information. Using a broad set of corporate events, we find that heterogeneity among the population of analysts causes their response to corporate news to be spread over several months. Long-term drift and return reversal following those events can be predicted at different horizons by the fraction of contrarian recommendations, i.e., recommendations that contradict the initial market reception of the news. Together, our findings highlight the role of analysts' stickiness in shaping long-term stock price reaction to corporate news.

Keywords: Security analysts, investor attention, post-announcement drift

1. Introduction

In an influential paper on the market reaction to dividend initiation and omission, Michaely, Thaler and Womack (1995) provide evidence of systematic investor *underreaction* to the disclosure of company news by showing that stock price continues to drift in the direction of the initial stock price reaction several months after the dividend announcement. Ten years earlier, De Bondt and Thaler (1985) showed precisely the opposite in their seminal paper on 'winners' and 'losers'. They showed that investors often *overreact* to the accumulation of bad news so that stock prices tend to exhibit reversal in the long run. The contradiction, of course, is only apparent. Investor psychology, whose introduction in Finance has been pioneered by Richard Thaler, may materialize in so many ways, from over-confidence to inattention, that its impact on stock price is likely variable.

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Michaely, Womack and Thaler (1995) thus conclude their paper with the "hope [that] future research will help us understand why the market appears to overreact in some circumstances and to underreact in others".

Subsequent papers have successfully managed to explain the theoretical co-existence of the two phenomena using a combination of investor over-confidence, self-attribution bias, and investor attention[2]. Regarding market reception to news announcements, there is a vast empirical literature that has confirmed Richard Thaler's central idea that investor behavioral biases, coupled with limits to arbitrage, have real persistent effects on asset prices. This literature focuses mainly on the news content (e.g., hard vs. soft information) and the condition of its arrival (e.g., at a time of high or low investor attention) to show that investors may temporarily under- or over-react to the news.[3] This initial (mis)reaction is later corrected by subsequent returns that exhibit predictability. While the context of news arrival has been widely studied, the exact mechanism by which stock price may drift or revert in the long-run is much less understood. In particular, why is the post-announcement drift so persistent, sometimes lasting for several months? What forces make investors realize their initial mistake and correct it long after the initial announcements?

In this study, we propose a simple mechanism by which the initial stock price reaction may survive or revert in the long run. This is based on sell-side analysts' strong tendency to *delay* their stock recommendation, thus creating a stock price response (whether a drift or a reversion) that takes time to materialize. Sell-side analysts are important information intermediaries who collect and interpret information about stocks and provide stock recommendations to their clients. Analyst's decision to issue a stock recommendation rests on comparing their own valuation of the stock (*V)* with the current stock price (*P*). When the ratio of the analyst's stock valuation to price (*V/P*) crosses certain thresholds, a revision of the current recommendation is called for (Bernhardt et al. 2016; Boulland et al. 2017). In this framework, new information about future cash-flows, for instance the announcement of a new product, an exceptional dividend or an earnings release, forces analysts to reconsider their own valuation *V* of the stock and to assess whether a revision is needed. New information arrival can also move the publicly traded share price (*P*), so that both *V* and *P* are affected

2 See for instance Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) and Hirshleifer (2001) for a survey.

3 See among other Della Vigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Peress (2008), and Engelberg (2008).

simultaneously (Conrad et al. 2006). In that case, analysts evaluate whether the stock price has fully incorporated the news content and an upgrade or a downgrade will result if they believe that the stock price underreacts or overreacts, respectively, to new information.

While in theory an analyst would issue a recommendation change as soon as the valuation-to-price ratio passes a threshold, prior research has shown that analysts are generally reluctant to change their outstanding recommendation, even in the presence of new information (Conrad et al 2006; Bernhardt et al. 2016). There are two main reasons that explain this stickiness, the reluctance of analysts to change their recommendation. The first is reputational concerns that drive analysts *not* to revise their recommendation too often. Indeed, analysts have a track record of recommendations that investors implicitly use to evaluate their stock-picking ability. In this context, changing their recommendation too often would signal that they were initially wrong (Trueman 1990). Therefore, an optimal behavior may be to adopt a signaling strategy where recommendations are revised only when analysts' private signal exceeds a certain value (Chen, Francis, and Jiang 2005). Such strategy can be achieved by setting excessively high thresholds that the valuation-to-price ratio needs to cross, so that revisions occur infrequently (Bernhardt et al. 2016).

The second source of stickiness in recommendation change comes from the frequency with which analysts update their own valuation of the stock V, which can be affected by several well-known *behavioral biases*. First, analysts may encounter difficulties in processing new information. Like investors who sometimes exhibit limited attention (Hirshleifer, Lim, and Teoh 2009), analysts may find it too costly to systematically analyze new information to assess whether a revision is needed. Here, the speed at which analysts update their own stock valuation V depends on the amount of resources they (or their brokerage house) allocate to a particular stock, and this difference in attention may potentially delay the issuance of a revision when new information arrives. Second, analysts may slow the issuance of a new recommendation because they act as overconfident agents with a self-attribution bias in the spirit of Daniel et al. (1998). In this framework, analysts collect private information, for instance through their interactions with the management, but they tend to overreact to this information. When confirming public events arrive, the self-attribution bias leads analysts to become more confident, while disconfirming events do not weaken their confidence. Only repeated negative signals correct the initial overreaction phase. In this framework, the combination of over-confidence

and self-attribution bias explains why analysts issue infrequent contrarian recommendations. Third, analysts may be slow to update their valuation following public news because they wait for signals that *complement* the news release. One of those complementary signals is the stock price reaction to news: similar to institutional investors who use feedback trading strategy (Sias and Starks 1997; Sias et al. 2001), following a news release, analysts may simply wait and upgrade (downgrade) stocks that performed well (poorly) after the news announcement. Another complementary signal that analysts follow can take the form of recommendations issued by other, more reputable, analysts consistent with models of herding (Scharfstein and Stein 1990).

We further hypothesize that there is heterogeneity among analysts in the stickiness they apply to their recommendations, so that after a news release, recommendation changes by analysts covering the stock will be spread over an interval of several months instead of occurring contemporaneously. We look at a broad set of corporate announcements (e.g., related to earnings, dividends, new product introductions, M&A transactions, etc.) for which at least one analyst covering the stock issues a recommendation in the ten days following the event. We study the time it takes for the other analysts covering the stock to respond to such news, by means of a recommendation change or a reiteration. We find that four calendar months after the event, on average, only half of the analysts covering the stock respond to such news and that it takes a total of nine months for all analysts to respond to the initial news. This is consistent with the existence of substantial heterogeneity among analysts in their propensity to react to news. We then look at the stock price implication of this delay in analysts' response. The essence of our results is depicted in Figure 1.

We graph the long-term stock price reaction to corporate news for which the initial return over a [-1; +1] window is positive (Fig. 1a). Announcements are divided into four quartiles based on the proportion of contrarian recommendations, i.e., recommendations that infirm the initial positive reception of the news by the market (for Fig. 1a, this ratio is #downgrade/#recommendation changes). The horizon for computing the long-term stock price reaction is 100 trading days, and the proportion of contrarian recommendations is computed by taking all recommendation changes up to this horizon. Corporate news in the lowest quartile of contrarian (the black triangles), containing mostly confirming recommendations, exhibit a strong and persistent post-announcement drift. By contrast, news in the highest quartile of contrarian (the gray

Figure 1a. Abnormal stock return following positive news announcements.

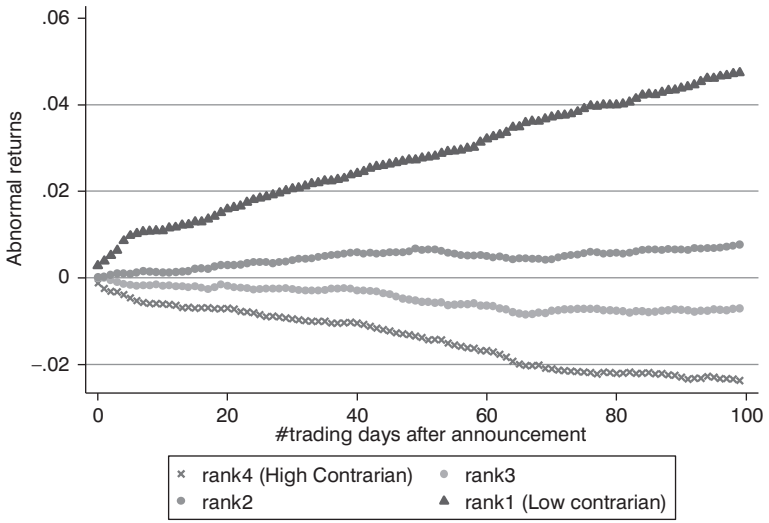
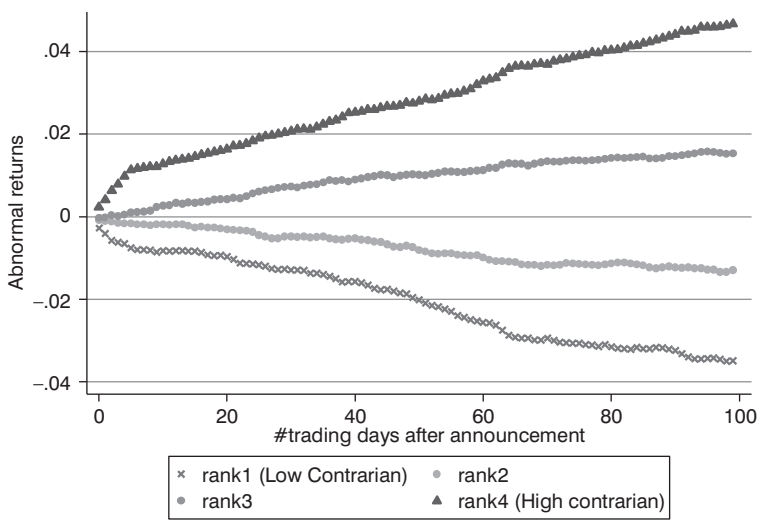


Figure 1b. Abnormal stock return following *negative* news announcements. The cumulative abnormal return for each news announcements is computed as the difference between the cumulative return of the stock and the cumulative return of the CRSP value-weighted market index. Announcements are divided into four quartiles based on the proportion of contrarian recommendations.



crosses) exhibit a return reversal that seems to materialize immediately. The two quartiles in between exhibit a reversal or a drift that materializes with less strength. A similar picture emerges for news initially received negatively by the market (Fig. 1b); news in the highest quartile of contrarian (mostly upgrade recommendations) exhibit a strong return reversal. This suggests that recommendation changes arriving sequentially rather than in bulk result in a delayed stock price reaction. Had all analysts reacted at the same time (e.g. in the few days following the event), the news content would have been incorporated immediately into stock price.

While this result sheds light on the impact of differing recommendation changes, it suffers from a look-ahead bias, in the sense that we use the ex-post number of contrarian recommendations to study the long-term stock reaction. We tackle this issue in a multivariate setting where the stock price at different horizons (1 month, 2 months, etc.) is regressed against the number of contrarian recommendations taken one month before. This also allows us to control for factors that simultaneously affect the stock price reaction to news. Our main conclusion is robust to the inclusion of control variables and fixed effects; one of the main drivers of the long-term reaction is the proportion of delayed contrarian recommendations.

Our paper builds on two streams of literature. First, we contribute to the literature on market reaction to corporate news. Research in this area has generally focused on well-defined events (e.g., earnings announcements, dividends, share repurchases) to study the information content at the time of announcement and whether subsequent returns continue to drift or revert. Several papers in this literature have thus used proxies for investor attention to show how it affects announcement returns as well as subsequent returns. Among others, Della Vigna and Pollet (2009) use Friday announcements as a proxy for low investor attention, Hirshleifer, Lim, and Teoh (2009) studies announcements on busy days, Peress (2008) studies announcements with high media coverage, and Engelberg (2008) studies earnings announcements with hard vs. soft information. In all those cases, investor inattention results in the immediate stock reaction to corporate news to be muted and continue to drift in the subsequent months. Regarding the long-term drift, it is generally admitted that slow information diffusion among the population of investors, coupled with limits to arbitrage, explains why the stock price takes so long to reflect the initial news. We contribute to this literature by studying one specific channel through which such a

delay occurs, namely, sell-side analysts' stickiness. Because investors often follow analyst recommendations when making portfolio choices, analysts' reluctance to update their stock recommendations creates such delayed pattern in stock price.

Second, we contribute to the literature on the role of sell-side analysts in capital markets, and particularly to the field that studies their investment value to investors (Womack, 1996; Barber et al. 2006). One view on sell-side analysts is that they simply proxy for market expectations; they do not provide any new information, and their recommendations mostly piggyback on existing news (Altınkılıç and Hansen 2009), although such conclusion is very sensitive to data inaccuracy (Bradley et al. 2014). Another view is that analysts, in addition to their information discovery role (Ivkovic and Jegadeesh, 2004) provide interpretation about corporate events, thus helping investors to make investment decisions (Livnat and Zhang 2012; Li et al. 2015; Rubin et al. 2017). Our paper provides evidence supporting the view that analysts help investors interpret information, but they do so only imperfectly. Building on the literature that studies analysts' decision-making (Conrad et al 2006, Bernhardt et al. 2016), we show that their reluctance to update their stock recommendations delay the incorporation of the news into stock prices. Analysts' stickiness has thus real and persistent effects on stock prices.

At a broader level, our paper connects with the field of Behavioral Finance that wishes to study "market" not as a single block, but as a collection of individuals with different information and incentives. In his 2016 presidential address to the American Economic Association ("Behavioral Economics: Past, Present, and Future"), Richard Thaler called for studying "Humans rather than Econs" (short for *Homo Economicus)*. We believe that our focus on one particular agent, sell-side analysts, fits within this agenda.

The rest of the paper is organized as follows. Section 1 develops our hypothesis. We describe the data and provide descriptive statistics in Section 2. Section 3 describes the empirical methodology. Section 4 presents the main results, and Section 5 concludes.

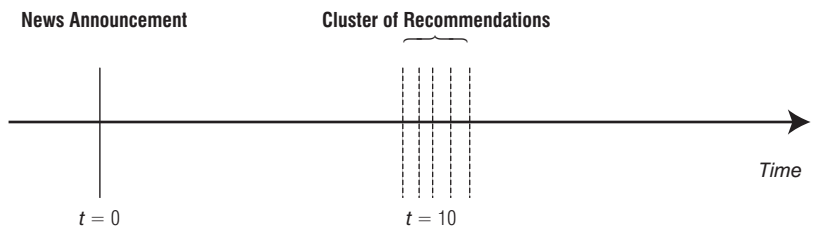
2. Background and Hypothesis Development

Our discussion suggests that analysts' stickiness stems from (1) frictions that analysts voluntarily set up to avoid frequent revisions and;

(2) behavioral biases (e.g., inattention) that lead them to delay the issuance of a recommendation update.

If there is no heterogeneity among analysts, i.e., analysts' behavior follows that of a representative analyst, recommendations following a news announcement should cluster in time. We represent this first situation in Figure 2a.

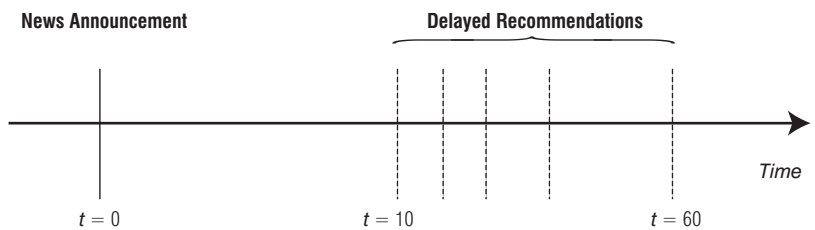
Figure 2a. Analyst response to news when there is no heterogeneity.



In fact, in a world without frictions, all recommendation should be issued at the announcement of the news because variations in the valuation-to-price ratio would force all analysts to update their recommendation immediately.

On the other hand, there are plausible reasons to believe that there is heterogeneity among analysts regarding the two factors driving recommendations' stickiness. For instance, some analysts may be more concerned about their career than others (Hong and Kubik, 2003), which leads them to set up higher thresholds for revision. Additionally, some analysts working for large brokerage firms may have better resources to monitor the news about stock prices, allowing them to respond quicker. Heterogeneity in the population of analysts should lead analysts to respond to a public announcement at different points in time. This is the situation described in Figure 2b.

Figure 2b. Analyst response to news when there is heterogeneity.



The above discussion leads us to hypothesize that if all analysts face equal frictions, recommendation revisions will cluster in time. Conversely, if there is heterogeneity among analysts, analysts' reaction to public news will be spread over several months. This is the first hypothesis that we test:

H1: Following a public announcement, analysts issue recommendation updates at different points in time.

Next, we hypothesize that because not all recommendations occur at the same time, such delays have a long-term impact on stock prices. In particular, return reversal should occur when the issuance of *contrarian* recommendations is delayed, and symmetrically the stock price should drift in the direction of the initial news when the issuance of *confirming* recommendations is delayed. This is the second hypothesis that we test.

H2: The long-term stock price reaction depends on the proportion of confirming vs. contrarian recommendations that are delayed.

Finally, we build on the literature that documents that analysts, in addition to their discovery role, have an *interpretation* role (Livnat and Zhang 2012; Rubin et al. 2017). We hypothesize that if investors are looking for an interpretation of the news -and especially how this news will affect future cash-flows- then the interpretation role of analysts should be more valuable when facing "soft" as opposed to "hard" news (Engelberg 2008). "Soft" news - for instance a change in executive or a new product introduction- may reflect on the stock price gradually and the impact on price may be ambiguous; conversely "hard" news -e.g. earnings announcements- are typically based on figures and their price impact tends to be more immediate. Our third hypothesis follows:

H3: The relation between delayed recommendations and the long-term stock price reaction is stronger for soft than for hard news.

3. Sample and Data

We collect analyst recommendations on U.S. stocks from I/B/E/S, and security-level information from CRSP. We keep only common stocks (share code 10 or 11) and we remove recommendations issued by anonymous analysts. Each recommendation is coded with a rating scale between 1 and 5, ranging from "strong buy" to "strong sell". A recommendation is

characterized as an upgrade (resp. a downgrade) if the revised recommendation has a higher (resp. lower) rating than the previous recommendation. Recommendation revisions that leave the rating unchanged are labelled as reiterations. Finally, we restrain the recommendation dataset to stock-year covered in the news flow dataset (see below). Our final sample covers the period 2003-2016. It includes 325,236 recommendations of which 96,225 are initiations of coverage; 81,167 are upgrades; 95,090 are downgrades; and 52,754 are reiterations.[4] In some tests, we use earnings forecasts issued by analysts. We thus collect one-year ahead earnings estimates issued by the same analysts on the same stocks over the same period (2.2 million earnings estimates).

We are primarily interested in how analysts delay the issuance of stock recommendations when confronted with new information. Therefore, it is critical for our purpose to obtain a sufficiently wide coverage of company news. Our main source for news flows is the Capital IQ's Key Development database (CIQ), a comprehensive database of company-specific news collected from various sources (e.g. newswire services, newspaper articles, or investor transcripts). We also supplement the Capital IQ dataset with earnings announcements news from the I/B/E/S actual file. Capital IQ classifies news into more than 100 different items. To ease the interpretation, we follow Boulland et al. (2017) and we aggregate those items into nine different categories: *Agenda communication*; *Earnings announcement*; *Management guidance*; *Product market and Strategy*; *Payout policy*; *Executive turnover*; *Securities issuance*; *Mergers & Acquisitions;* and *Legal issues*. The Capital IQ-I/B/E/S combined dataset has more than two million observations over the period 2003-2016. We apply various filters to this dataset. First, in the original CIQ dataset, about one third of the news consists in communications about the date of forthcoming corporate events (e.g., investor day, annual meetings, etc.). We remove them from the dataset. Second, we remove stock-year observations covered by less than three analysts. Third, we keep only news for which at least one analyst has issued a recommendation in the 10 days following the announcement. While this last filter removes more than 20% of the news, it ensures that we are considering only news that are sufficiently important that they trigger at least one analyst recommendation. The final dataset contains 175,927 news announcements covering 4,891

4 Because of the sample period, our dataset is free from the mechanical recommendation changes due to the implementation of the 2002 Global Settlement documented in Kadan et al. (2009).

Table 1. Sample selection and corporate news description

This table reports details on the sample selection of corporate news. The sample of news consists of the Capital IQ's Key Development database (CIQ), a comprehensive database of company-specific news. We supplement the CIQ dataset with Earnings announcements from the I/B/E/S actual file. The sample period is 2003-2016. Capital IQ classifies news into more than 100 different items. We aggregate those items into eight different categories: *Earnings announcement; Management guidance; Product market & Strategy; Payout policy; Executive turnover; Securities issuance; Mergers & Acquisitions;* and *Legal issues*. In Panel A, we provide details on the selection of news. In Panel B, we provide the frequency of each news type in the final sample.

Panel A: Sample selection.	
Capital IQ -I/B/E/S dataset	2,092,586
- Agenda communication	547,847
- Stock-year covered by less than 3 analysts	930,816
- News with no recommendations within 10 days	437,996
#News announcements	175,927
# Distinct stocks	4,891

Panel B: Frequency of news.		
News type	**Nobs.**	**Proportion**
Product Market & Strategy	48,148	27%
Earnings announcements	26,025	15%
Management guidance	19,670	11%
Executive turnover	18,731	11%
M&A	18,631	11%
Payout policy	9,142	5%
Securities issuance	8,114	5%
Legal issues	7,034	4%
Other	20,432	12%
Total	175,927	100%

distinct stocks. Table 1 Panel A describes the sample selection and Panel B provides the frequency of each news type. The largest group is *Product Market & Strategy* (which includes items such as strategic alliances or client announcements) followed by *Earnings Announcements* and *Management Guidance*.

We merge the final news dataset with firm-level accounting data from COMPUSTAT and we compute the following variables: *Return on Assets*, *Return on Equity*, *Earnings per share*, *Market-to-Book*, *Market value of equity*. To limit the effect of outliers, all variables are winsorized at the 1% in each

Table 2. Sample descriptive

This table displays characteristics of announcing firms over the 2003-2016 period. The sample includes all U.S. firms in the CIQ-I/B/E/S combined dataset. In Panel A, we present characteristics across firms along several variables. *ROA* is net income for fiscal year t divided by total assets for fiscal year t. *ROE* is net income for fiscal year t divided by common equity for fiscal year t-1. *EPS* is earnings per share (in $). *Assets* is total assets on Q4. *Market value of equity* is the monthly average market value measured in December of fiscal year t. *Market-to-Book* is the ratio of market equity for fiscal year t to book value of equity for fiscal year t. All continuous variables are winsorized at the 1% level in each tail. In Panel B, we display the correlation matrix of the main variables used.

Panel A: Summary statistics

	Mean	Std. Dev.	p25	p50	p75	N
ROA	0.68%	0.11	0.09%	1.08%	2.50%	171,032
ROE	0.40%	1.24	0.21%	3.20%	5.50%	171,002
EPS ($)	0.34	0.75	0.02	0.29	0.66	171,065
Market-to-Book	3.88	9.52	1.53	2.66	4.51	170,993
Assets ($ million)	20,621	40,332	849	3,601	16,419	171,152
Market value of equity ($ million)	12,683	18,249	1,050	3,712	15,155	171,125

Panel B: Correlation matrix

	ROA	ROE	EPS ($)	Assets	MV	MTB
ROA	1					
ROE	–0.01	1				
EPS ($)	0.29	0.04	1			
Assets	0.01	0.00	0.13	1		
Market value of equity [MV]	0.06	0.01	0.23	0.70	1	
Market-to-Book [MTB]	0.06	0.14	0.02	–0.07	0.04	1

tail. Table 1 Panel A provides summary statistics of our sample of firms and Panel B displays the correlation matrix of the main variables used.

4. Empirical Methodology

4.1. Measuring the response delay to public news

Our first hypothesis states that if there is heterogeneity among analysts in the frictions they face, recommendation revisions by the whole population

of analysts will be spread over several months. We empirically examine this question by computing a Response Ratio (RR) following public announcements (Rubin, Segal, and Segal 2017). For a given news *n* on a stock *i*, we define the H-day response ratio (*RR*) as follows:

$$RR_{n,i}(t,t+H) = \#reco_{n,i}(t,t+H) \tag{1}$$

where $\#reco_{n,i}(t,t+H)$ is the number of recommendations issued on stock *i* from day *t* to day *t+H* after the news. To compute this ratio, for each news in our dataset we count the cumulative number of recommendations issued on the stock from the announcement day (*t=0*) to various horizons up to 300 calendar days. We include in the computation of the ratio both recommendation changes and reiterations. Next, we scale this number by either: *i*) analyst following on the year prior to the news announcement, or *ii*) by the cumulative number of recommendations 300 calendar days after the news. The first measure aims at answering the following question: given that ex-ante, there are *x* analysts following the stock, how long does it take for them to respond to a major news about the firm? One issue with this measure is that analyst following -i.e. the population of analysts who *actively* follow the stock- may be affected by the news flow, so that analyst following on the year prior is not necessarily a good proxy for analyst following at the time of the news announcement. This issue is addressed by the second measure which scales the Response Ratio by the ex-post number of recommendations.

4.2. Measuring the impact of response delay to public news on stock return

Our second hypothesis states that the long-term stock price behavior (drift or return reversal) depends on the proportion of *confirming* vs. *contrarian* recommendations that are delayed. To test this hypothesis, for each news announcement, we compute the *H*–day buy–and–hold abnormal returns (*BHAR*) from time *t* to time *t+H* as follows:

$$BHAR_i(t,t+H) = \prod_{\tau=t}^{t+H}\left(1+R_{\mathrm{i},\tau}\right) - \prod_{\tau=t}^{t+H}\left(1+R_{\mathrm{m},\tau}\right) \tag{2}$$

where $R_{\mathrm{i},\tau}$ is the raw return on stock i on day τ, and $R_{\mathrm{m},\tau}$ is the return on the C/R/S/P value-weighted market index.

There are no clear-cut measures for post-announcement drift or return reversal, in particular regarding the horizon to be chosen for looking at

those two phenomena. The central idea -expressed in Michaely, Thaler, and Womack (1995)- is whether the subsequent returns confirm the initial stock price reaction (a sign of *underreaction*) or whether they revert in the long run (a sign of an initial *overreaction*). For this reason, we consider the return at the announcement date to represent the initial reception of the news by the market. Positive (resp. negative) return at announcement signals that the market as a whole considers it to be a good (resp. a bad) news. We thus partition the news into *Positive* or *Negative* based on the sign of the buy-and-hold abnormal returns around the announcement date.

Next, we turn our attention to the measure of confirming vs. contrarian recommendations. We define a *contrarian* recommendation to be a recommendation change that contradicts the initial market reception of the news: it is a downgrade for positive news and an upgrade for negative news. We define the Contrarian Ratio (CR) in a similar fashion to the Response Ratio in Eq. (1):

$$\mathrm{CR}_{\mathrm{n,i}}(t,t+H) = \begin{cases} \dfrac{\#\,\mathrm{downgrades}_{\mathrm{n,i}}(\mathrm{t},\mathrm{t}+\mathrm{H})}{\#\,\mathrm{reco}_{\mathrm{n,i}}(\mathrm{t},\mathrm{t}+\mathrm{H})} \;\; if \;\; Positive_{n,i} = 1 \\ \dfrac{\#\,\mathrm{upgrades}_{\mathrm{n,i}}(\mathrm{t},\mathrm{t}+\mathrm{H})}{\#\,\mathrm{reco}_{\mathrm{n,i}}(\mathrm{t},\mathrm{t}+\mathrm{H})} \;\; if \;\; Positive_{n,i} = 0 \end{cases} \tag{3}$$

where $Positive_{n,i}$ is a dummy variable equal to 1 (resp. equal to 0) for positive (resp. negative) news; $\#\,downgrades_{n,i}(t,t+H)$ (resp. $\#\,upgrades_{n,i}$) is the number of downgrades (resp. upgrades) issued on stock i from day t to day $t+H$ after the news; and $\#\,reco_{n,i}(t,t+H)$ is the number of recommendations issued on stock i over the same period. Here, we consider only recommendation changes (upgrades and downgrades) and remove reiterations, so that the Contrarian Ratio takes value between 0 and 1. Higher value of this number indicates strong ex-post disagreement from analysts about the initial market reception of the news.

To ease the interpretation, we form four quartiles of the Contrarian Ratio based on an annual sort from quartile 1 (*Low* contrarian) to quartile 4 (*High* contrarian). We first look at the relation between future stock return and the contrarian ratio by double sorting news with respect to: 1) *Positive* vs. *Negative* news; and 2) the four quartiles of the Contrarian Ratio. Each news thus falls into one of the eight (2x4) portfolios and we compute the buy-and-hold abnormal returns at different horizons for each portfolio.

Next, to account for factors that could simultaneously explain the reaction to news, we turn to a multivariate regression setting. We estimate various specifications of the following equation:

$$BHAR_{n,i,y}[\mathrm{t},\mathrm{t}+\mathrm{H}] = \alpha_0 + \alpha_{CR}.Q_{n,i}[\tau;\mathrm{T}] + \sum_{\mathrm{k}=1}^{\mathrm{K}}\beta_{\mathrm{k}}.\mathrm{C}^{\mathrm{k}}_{\mathrm{i,y-1}} + \varepsilon_{\mathrm{n,i}} \qquad (4)$$

where $BHAR_{n,i,y}[\mathrm{t},\mathrm{t}+\mathrm{H}]$ is the abnormal stock return of firm i in year y from day t to day $t+H$ following the news announcement n. The variable $Q_{n,i}$ represents the four quartiles of the Contrarian Ratio $CR_{n,i}$, introduced as a continuous variable (from $Q_{n,i}=1$ to $Q_{n,i}=4$). The Contrarian Ratio is measured over a $[\tau;\mathrm{T}]$ window that ends before the $[t;t+H]$ window for computing abnormal returns. Our interest is in the coefficient α_{CR} which measures the average effect on subsequent returns of a one-quartile increase in the Contrarian Ratio. We posit that higher (resp. lower) values of the Contrarian Ratio leads the return to revert (resp. drift) in the medium to long run. Therefore, we expect α_{CR} to be negative for positive news, and to be positive for negative news.

We allow the stock price response to depend on a set of K control variables $C^{k}_{i,y-1}$. We include *Market Capitalization* as a proxy for size, *Return On Assets* as a proxy for profitability, and *Market-to-book* as a proxy for the existence of growth opportunities. All variables are computed on year-end date prior to the news announcements (year *y-1)*. The coefficient α_0 includes a set of various fixed effects that controls for time trend in stock price response (year fixed effects) and unobserved heterogeneity at the stock level (stock fixed effects). Finally, we allow the residuals $\varepsilon_{n,i}$ to be correlated for the same stock and compute standard errors adjusted for heterogeneity and within-stock clustering (Petersen, 2009).

4.3. Cross-section according to Soft vs. hard information

Our third hypothesis states that the relation between delayed recommendations and the long-term stock price reaction is stronger for soft than for hard news. We exploit the classification provided by the Capital IQ dataset to allocate news into the "soft" or the "hard" news category. We consider that *Earnings Announcements* and *Payout Policy* fall into the "hard" news category because their announcements come with figures that are highly scrutinized by the market. By contrast, we consider into

the "soft" information category the following news: *Product market & Strategy*, *Executive turnover,* and *M&A*. To test hypothesis *H3*, we estimate a modified version of Eq. (4) where we add interaction terms. Specifically, we estimate the following equation:

$$BHAR_{n,i,y}[\mathrm{t},\mathrm{t}+\mathrm{H}] = \alpha_0 + \alpha_{CR}.Q_{n,i}[\tau;\mathrm{T}] + \alpha_{\mathrm{S}}.Soft_{n,i} + \beta_{CR}.Q_{n,i}[\tau;\mathrm{T}] * Soft_{n,i} + \sum_{\mathrm{k}=1}^{\mathrm{K}}\beta_{\mathrm{k}}.\mathrm{C}^{\mathrm{k}}_{\mathrm{i,y}-1} + \sum_{\mathrm{k}=1}^{\mathrm{K}}\delta_{\mathrm{k}}.\mathrm{C}^{\mathrm{k}}_{\mathrm{i,y}-1} * Soft_{n,i} + \varepsilon_{\mathrm{n,i}} \quad (5)$$

where $Soft_{n,i}$ is a dummy variable equals to one if the news n on stock i is classified as "soft" and which is otherwise equal to zero if the news is classified as "hard". We interact this dummy with the four quartiles of the Contrarian Ratio as well as with all control variables; they are represented by the term $\sum_{\mathrm{k}=1}^{\mathrm{K}}\cdot_{\mathrm{k}}.\mathrm{C}^{\mathrm{k}}_{\mathrm{i,y}-1} * Soft_{n,i}$ in Eq. (5). Our interest is in the coefficient β_{CR}, which measures the incremental difference in the stock price reaction to contrarian recommendations for *Soft* vs. *Hard* news.

5. Results

5.1. Analysts' response to news

The first hypothesis (*H1*) states that heterogeneity among analysts causes recommendations after a news announcement to be spread over several months. We examine this hypothesis in Table 3.

Panel A reports the Response Ratio of Eq.(1) at different horizons. The first measure -the Response Ratio scaled by analyst following- shows that it takes about three months (90 calendar days) for half of the analysts to issue a recommendation change or a reiteration and that it takes nine months (240 calendar days) for all analysts to respond to the initial news. The second measure –Response Ratio scaled by *ex-post* number of recommendations- yields quantitatively similar conclusion: four months after the news, 50% of total recommendations observed were issued.

Next, we study whether analysts' response speed depends on the type of news announced. One could assume that analysts would be particularly

diligent in responding to major news such as earnings announcements, while delaying their stock recommendations for softer news (e.g., those related to strategy and product market). In Panel B, we compute the response rate of analysts for the eight different types of news and we find that the response rate is similar across all types. It suggests that analysts may use other outputs than recommendations (for instance earnings forecasts) in regard to providing timely update about a well-followed, pre-scheduled event such as earnings announcements.

Relatedly, a plausible reason why analysts would voluntarily delay the issuance of new recommendations is because earnings forecasts and recommendations target two different audiences.[5] Malmendier and Shantikumar (2014) suggest that retail investors follow recommendations while institutional investors follow earnings estimate updates. In this context, analysts could choose to issue timely earnings forecasts to show their ability to large investors, while delaying the issuance of recommendations. We examine the timing of earnings forecasts vs. recommendation changes in Panel C. For each recommendation change (upgrades and downgrades), we check whether there is an update to earnings estimate issued on the same day as change in recommendation is issued (Kecskés et al. 2016). When there are no contemporaneous earnings forecasts, we check whether the analyst has issued one in the weeks preceding the recommendation change. The latter case would signal an attempt to grant large investors early access to future recommendations by changing an output -earnings estimate- that is presumably more scrutinized by them. Panel C shows that 14% of upgrades (13% of downgrades) fall into this category. It suggests that one reason why some analysts delay their recommendations is to cater to a specific investor audience. However, this strategy by itself does not explain the tendency of all analysts to delay their recommendation, which supports the idea that there are several biases that affect the stickiness of analysts to their recommendations.

We conclude that analysts' heterogeneity in their response to news indeed results in recommendations that are spread over several months. This finding is in line with previous literature that documents that analysts infrequently update their recommendation (Conrad et al. 2006; Bernhardt et al. 2016; Boulland et al. 2017). The unusually long time it takes for some analysts to respond (almost eight months) calls for some

5 We thank an anonymous referee for suggesting this interpretation to us.

Table 3. Analyst response to corporate news announcement

This table reports summary statistics on analyst response to news announcement at different horizons. The sample includes all U.S. firms in the CIQ-I/B/E/S combined dataset over the period 2003-2016. The sample includes 175,927 news announcements for which at least one analyst recommendation has been issued in the 10 days following the announcement. In Panel A and B, we compute the Response Ratio (Eq.1) scaled by either: i) ex-ante analyst following on the year preceding the news (year *t-1*); ii) the number of recommendations after 300 days. In Panel A and B, the recommendation sample includes both recommendation changes and reiterations. In Panel C, the recommendation sample includes only recommendation changes.

Panel A: Average number of recommendations following news announcements at different horizons.

	#recommendations issued by analysts at different horizons											
#days after announcement	10	20	30	60	90	120	150	180	210	240	270	300
% of analyst following	17%	21%	25%	36%	48%	61%	72%	84%	96%	107%	118%	130%
% of ex-post #recommendations	16%	19%	22%	31%	40%	49%	58%	66%	75%	83%	91%	100%

Panel B: Average number of recommendations following news announcements at different horizons for each type of news.

	#recommendations issued by analysts at different horizons											
#days after announcement	10	20	30	60	90	120	150	180	210	240	270	300
Product Market & Strategy	14%	17%	20%	29%	39%	48%	57%	65%	74%	83%	91%	100%
Earnings announcements	20%	23%	25%	33%	43%	52%	60%	68%	77%	84%	92%	100%
Management guidance	17%	20%	22%	31%	40%	49%	57%	66%	75%	83%	91%	100%
Executive turnover	15%	18%	21%	30%	39%	49%	57%	66%	75%	83%	92%	100%
M&A	17%	21%	24%	33%	42%	51%	59%	67%	76%	84%	92%	100%
Payout policy	16%	19%	22%	30%	40%	49%	57%	66%	75%	83%	91%	100%
Securities issuance	15%	18%	21%	31%	40%	49%	58%	66%	75%	84%	92%	100%
Legal issues	13%	16%	20%	29%	39%	48%	57%	66%	75%	83%	91%	100%

Panel C: Timing of earnings forecasts prior to recommendation changes.

	Nobs.	Proportion
All upgrades	81,167	100%
With a contemporaneous earnings estimate *increase*	28,825	36%
With a contemporaneous earnings estimate *decrease*	13,894	17%
With an earnings forecast between the reco. and the news	11,600	14%
Without earnings forecasts	26,848	33%
All downgrades	95,090	100%
With a contemporaneous earnings estimate *decrease*	31,913	34%
With a contemporaneous earnings estimate *increase*	19,134	20%
With an earnings forecast between the reco. and the news	12,444	13%
Without earnings forecasts	31,599	33%

comments. At one extreme, we find analysts who are quick to update their own stock valuation, and consequently their recommendations, as soon as news comes in. On the other extreme, some analysts are slow-updaters. For this to occur, they do not need to react necessarily to the *exact* same piece of information as fast-updater analysts. For instance, some analysts may stick to their recommendation because when the news arrives, they are inattentive, or they have changed their recommendation recently so that they are reluctant to change it again. After a few months pass, they observe that the stock price has increased -perhaps as a consequence of the initial news announcement- and that other analysts covering the same stock have changed their recommendation. This forces them to look back at the stock history, including the initial news; if they believe that the stock has still some upside potential they will upgrade their recommendation. Such behavior is consistent with the general idea that analysts often *herd* (Welch, 2000) or that, similar to institutional investors, they may use feedback trading strategy when deciding to issue an update to their recommendation (Sias and Starks, 1997). In the above scenario, after several months have passed, the analysts do not respond to the news alone but to a mix of the initial news, its associated stock return over the last months, and the behavior of their peers.

5.2. Analysts' response and the post-announcement drift: ex-post analysis

We now turn our attention to the impact of such delay on the drift and/or return reversal following news announcement (hypothesis *H2*). In Table 4, we look at the unconditional long-term stock price reaction following news announcements. We partition the news into *Positive* and *Negative* and compute the subsequent abnormal returns (Eq. 2). If the stock price fully reflects the news content, then there should be no return predictability based on this partitioning. On the other hand, under- or over-reaction would generate a predictable pattern in stock return. To account for possible information leakage prior to the announcement as well as to account for any delayed news access by some investors, we partition the sample according to the return around a (-1;+1) window. Next, we compute abnormal returns at different horizons: 3 months (65 trading days), five months (107 days), seven months (149 days), and 10 months (212 days).

Panel A shows that following positive news, the stock prices continues to rise: the 3-month excess return is significant at 5%, significantly different

Table 4. Contrarian recommendations and the post -announcement drift

This table reports cumulative buy–and–hold abnormal returns following news announcements. The sample includes all U.S. firms in the CIQ-I/B/E/S combined dataset over the period 2003-2016. The sample includes 175,927 news announcements for which at least one analyst recommendation has been issued in the 10 days following the announcement. We compute *H*–day buy–and–hold abnormal returns (BHAR) using the C/R/S/P value-weighted market index. In Panel A, we sort the results with respect to *Positive* and *Negative* news. In Panel B, we double-sort the results with respect to: (1) *Positive* vs. *Negative*, and (2) *High* vs. *Low* contrarian. Heteroskedasticity–adjusted standard error is reported in parenthesis below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Long-term stock price reaction following news announcement.					
	Buy-and-hold abnormal returns over different windows (trading days)				
	(0,0)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Positive	0.018***	0.050***	0.056***	0.060***	0.066***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Negative	–0.016***	–0.034***	–0.032***	–0.029***	–0.025***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Positive vs. Negative	0.034***	0.084***	0.088***	0.089***	0.091***

Panel B: Long-term stock price reaction conditional on contrarian recommendations.					
	Buy-and-hold abnormal returns over different windows (trading days)				
	(0,0)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Positive news					
nq=1 (Low contrarian)	0.017***	0.087***	0.106***	0.123***	0.151***
	(0.000)	(0.002)	(0.003)	(0.004)	(0.004)
nq=2	0.016***	0.065***	0.081***	0.093***	0.106***
	(0.000)	(0.002)	(0.003)	(0.003)	(0.004)
nq=3	0.016***	0.038***	0.041***	0.040***	0.042***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.003)
nq=4 (High contrarian)	0.022***	0.022***	0.014***	0.006**	–0.006**
	(0.000)	(0.002)	(0.002)	(0.002)	(0.003)
Low vs. High	–0.005***	0.065***	0.092***	0.117***	0.157***
Negative news					
nq=1 (Low contrarian)	–0.018***	–0.080***	–0.091***	–0.103***	–0.120***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.003)
nq=2	–0.015***	–0.043***	–0.045***	–0.048***	–0.048***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)
nq=3	–0.015***	–0.010***	–0.002	0.008***	0.023***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.003)
nq=4 (High contrarian)	–0.014***	0.010***	0.029***	0.047***	0.072***
	(0.000)	(0.002)	(0.002)	(0.003)	(0.004)
Low vs. High	–0.004***	–0.09***	–0.12***	–0.15***	–0.192***

from zero, and to be compared with an initial reaction of 1.8%. The drift is persistent, albeit less strong, up to 212 days with a return of 6.6%. For negative news, we observe a drift in the opposite direction: the 3-month return is -3.4%, compared with an initial -1.6% return. The drift seems to vanish afterward and abnormal returns exhibit a reversal at 212 days (-2.5%). Overall, accross a broad set of corporate events, we find evidence of a strong post-announcement drift for positive news. For negative news, we find only modest evidence of a drift, and some evidence of return reversal in the long run. These stock price patterns are consistent with the many studies that document predictable returns following specific corporate events such as dividend initiations and omissions (Michaely, Thaler and Womack 1995), stock splits (Ikenberry, Rankine, and Stice 1996), seasoned equity offerings (Loughran and Ritter 1995), or earnings announcements (Bernard and Thomas 1990).

In Panel B, we explore whether those patterns in the long-term return can be explained by analysts' activity computed over a large window following the event. We compute the Contrarian Ratio (Eq.3) over a 10 month (212 trading days) window following the event. We form four quartiles of the Contrarian Ratio based on an annual sort from quartile 1 (*Low* contrarian) to quartile 4 (*High* contrarian), and we double sort based on this variable and the *Positive* vs. *Negative* news dummy.

The impact of including this variable into the previous portfolio sorting is extremely large. For positive news in the lowest quartile of contrarian, the stock price jumps from 1.7% at announcement to a cumulative return of 15% at 212 days. Symmetrically, for positive news in the highest quartile of contrarian, the stock return exhibits a reversal with a 2.2% return at announcement and a -0.6% return after 10 months. The picture is similar for negative news: news in the lowest quartile of contrarian exhibit a strong and persistent drift (from -1.8% to -12% after 10 months), while news in the highest quartile of contrarian exhibit a strong return reversal with a positive return of 7.2% after 212 days.

In fact, this table suggests that *ex-post*, i.e., 10 months after the initial announcement of the news, the best explanation for long-term stock returns -whether a drift or return reversal- is the manner in which analysts have been interpreting the news and modifying their recommendations accordingly. This effect is consistent with previous studies that show that analyst recommendations are highly scrutinized by investors and have a marked

impact on stock returns (Womack 1996, Barber 2006). Consequently, the tendency of analysts to delay their stock recommendations for several months contribute to generate a drift or a return reversal. Had all the analysts modified their recommendation at the announcement of the news, such patterns would have probably been less discernable.

5.3. Analysts' response and the post-announcement drift: ex-ante analysis

A major issue with our methodology is that it suffers from a look-ahead bias because we look *ex-post* at the type of recommendations issued by analyst. However, it could well be that those recommendations simply represent market expectations about the stocks at different point in time, that is those recommendations do not deliver any new interpretation about the stock (Altinkilic and Hansen 2009). By contrast, we would like to study whether the accumulation of contrarian versus confirming recommendations at a given point in time can move the market, that is whether those recommendations are influential. If so, then the proportion of contrarian recommendations should *predict* future stock return.

We turn to this question by estimating the model described in Eq.(4) where the dependent variable is the buy-and-hold abnormal return at different time horizons considered above and the main independent variable is the proportion of contrarian recommendations one month *prior* (e.g., for the three-month horizon, we consider recommendations issued up to two months). Table 5 presents the results.

In Panel A, we present the results for positive news. The Contrarian Ratio is as before divided into quartiles, and those four quartiles are introduced as a continuous measure, so as to measure the average effect of a one-quartile increase in contrarian recommendations on stock returns at different horizons. Specifications (1) to (4) includes only year fixed effects. The coefficient on contrarian is as expected negative, and highly statistically significant for all the time windows considered. In term of economic magnitude, for the (0;65) window, a one quartile increase in the Contrarian Ratio translates into a 3.3% drop in stock return a month after. The magnitude and statistical significance of contrarian is similar for all the time windows (ranging from -3.3% to -3.7%). In Panel B, we present the results for negative news. The results are exactly symmetric. For instance, for the (0;65) window, a one quartile increase in the Contrarian Ratio translates into a 3.4% increase in stock return a month after,

Table 5. Stock price reactions to news announcements

This table presents OLS regressions examining the effect of contrarian recommendations on abnormal returns following news announcements. The dependent variable is the *H*-day buy-and-hold abnormal returns of the stock return over the daily C/R/S/P value-weighted return. We present the results separately for *Positive* (Panel A) and *Negative* news (Panel B). In both panels, the main independent variable is *Contrarian_rank*, the four annual quartiles of the Contrarian Ratio, introduced as a continuous variable. (*Contrarian_rank*=1 for the lowest quartile; *Contrarian_rank*=4 for the highest quartile). Control variables include *Market Capitalization*, *Return on Assets* (*ROA*), and *Tobin's Q*. Coefficient estimates on *Market Capitalization* are expressed in basis points. Standard errors are adjusted for heteroskedasticity and clustered by stocks. They are displayed below the coefficient estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: News with an initial positive market reaction.								
	Dependent variable: buy-and-hold abnormal return over different windows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+65)	(0,+107)	(0,+149)	(0,+212)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Contrarian_rank	–0.033***	–0.032***	–0.033***	–0.037***	–0.033***	–0.031***	–0.031***	–0.034***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Market Cap.					0.009***	0.010**	0.006	–0.012
					(0.003)	(0.005)	(0.006)	(0.008)
ROA					0.266***	0.407***	0.406***	0.498***
					(0.059)	(0.077)	(0.095)	(0.118)
Market-to-Book					0.001***	0.001***	0.001***	0.001*
					(0.000)	(0.000)	(0.001)	(0.001)
Constant	–0.023***	–0.016***	–0.015***	–0.016***	0.021***	0.056***	0.089***	0.106***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)	(0.011)	(0.013)	(0.016)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	69,841	69,843	69,844	69,845	69,739	69,741	69,742	69,743

Panel B: News with an initial negative market reaction.								
	Dependent variable: buy-and-hold abnormal return over different windows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+65)	(0,+107)	(0,+149)	(0,+212)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Contrarian_rank	0.034***	0.033***	0.033***	0.035***	0.027***	0.023***	0.022***	0.021***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Market Cap.					0.018***	0.020***	0.014**	–0.004
					(0.003)	(0.006)	(0.007)	(0.008)
ROA					0.188***	0.307***	0.363***	0.344***
					(0.072)	(0.081)	(0.102)	(0.115)
Market-to-Book					0.001***	0.002***	0.002***	0.002***
					(0.000)	(0.000)	(0.001)	(0.001)
Constant	–0.108***	–0.104***	–0.103***	–0.102***	–0.080***	–0.048***	–0.016	0.017
	(0.003)	(0.004)	(0.005)	(0.007)	(0.006)	(0.010)	(0.013)	(0.016)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	71,736	71,736	71,736	71,736	71,628	71,628	71,628	71,628

and coefficients estimates are similar across all the windows considered. In specifications (5) to (8), we introduce control variables that may affect the market response to news, namely *Market Capitalization*, *Return On Assets*, and *Market-to-book*, computed on year-end date prior to the news announcements. We also introduce stock fixed effects to control for unobserved heterogeneity at the stock level. The introduction of those controls does not affect neither the economic magnitude nor the statistical significance of the contrarian variable for *Positive* as well as for *Negative* news. Together, our results indicate that the one-month ahead level of contrarian recommendations can predict the stock returns following a public announcement. Our findings support the idea that analysts, rather than simply 'piggybacking' on news, have the ability to move the market by delivering value-relevant information (Loh and Stulz 2010, Bradley et al. 2014, Li et al. 2015).

5.4. Analysts' response and the post-announcement drift: robustness tests.

We explore the robustness of this result in Table 5 by applying several filters to our data. One concern is that the way we measure *Positive* vs. *Negative* news is based on an examination of the sign of the announcement return. It has to be acknowledged that such a method would lead to misclassification for news for which the return at announcement is close to zero. To address this issue, we focus on news that can unambiguously be mapped to positive or negative return by removing news for which the return is in the bottom (resp. top) 10% of the distribution of positive (resp. negative) news. We then estimate the model described in Eq.(4) on this subsample of news. The results are displayed in columns (1) to (4) of Table 6. It shows that the results are virtually unchanged when using this alternative measure of *Positive* vs. *Negative* news.

A second issue is that a piece of news by one firm can overlap with conflicting news issued by the same firm shortly after. This would be the case if firms are strategic in their disclosures. For instance, a few days after disclosing disappointing earnings, a firm may decide to issue optimistic earnings guidance to counterbalance the negative effect of the earnings announcement. In this context, an analyst aware of this tactic may delay the issuance of a contrarian recommendation simply because he is waiting for those counterbalancing news to be disclosed. If this is the case, we cannot solely attribute the return reversal to the recommendations by analysts.

We address this issue by filtering out news that are followed by a conflicting news in the two months following the initial news disclosure, and re-estimate Eq.(4) on this subsample of news. The results are displayed in columns (5) to (8) of Table 6. They show that the results are largely unchanged for positive news. For negative news, the coefficients are slightly lower in magnitude but they remain highly significant.

5.5. Cross-sectional analysis according to soft versus hard information

Our last hypothesis (*H3*) states that the relation between delayed recommendations and the long-term stock price reaction should be stronger when investors are facing "soft" news. We test this hypothesis by running a cross-sectional regression according to soft vs. hard news (Eq.5). Table 7 displays the results.

We find for *Positive* news (Panel A) that on average the correlation between contrarian recommendations and future returns is one percentage point higher (-1%) for soft information as opposed to hard information. This higher correlation holds until a seven-month horizon (149 days) and it is robust to the inclusion of control variables. For *Negative* news (Panel B), there is also a higher correlation between contrarian recommendations and future returns for soft as opposed to hard news. Nevertheless, the effect is much weaker (+0.4%) and it does not survive after three months. This suggests that the interpretation role of analyst matters less for negative news, perhaps because negative news are more quickly impounded into stock prices.

This highlight the fact that analysts, in addition to their discovery role, have an *interpretation* role (Livnat and Zhang 2012; Rubin et al. 2016). Together our results confirm that one possible channel by which accumulated contrarian recommendations impacts future returns is through the interpretation role of analysts.

6. Conclusion

Our paper explores the impact of analysts' tendency to delay their stock recommendations on two well-establishedanomalies: the drift following announcements of public news and return reversal (De Bondt and Thaler, 1985; Michaely, Thaler, and Womack 1995). We hypothesize and find that

Table 6. Stock price reactions to news announcements: robustness tests

This table presents robustness tests for the specifications in Table 5. In columns (1) to (4) of Panel A and B, we use an alternative measure of *Positive* and *Negative* news. For *Positive* (resp. *Negative*) we exclude news for which the return is in the bottom (resp. top) 10% of the distribution of positive (resp. negative) news. In columns (5) to (8), we remove news that are followed by a conflicting news in the two months following the initial news disclosure. Standard errors are adjusted for heteroskedasticity and clustered by stocks. They are displayed below the coefficient estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: News with an initial positive market reaction.								
	Alternative measure of *Positive news*				Excluding overlapping news			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+65)	(0,+107)	(0,+149)	(0,+212)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Contrarian_rank	–0.033***	–0.031***	–0.031***	–0.035***	–0.030***	–0.029***	–0.030***	–0.036***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Market Cap.	0.009**	0.010*	0.005	–0.013	0.005	0.006	0.001	–0.019***
	(0.004)	(0.005)	(0.007)	(0.009)	(0.003)	(0.004)	(0.005)	(0.007)
ROA	0.266***	0.404***	0.400***	0.495***	0.216**	0.364***	0.340***	0.392***
	(0.060)	(0.079)	(0.097)	(0.119)	(0.087)	(0.093)	(0.113)	(0.128)
Market-to-Book	0.001***	0.001***	0.001**	0.001*	0.001***	0.001***	0.001***	0.002**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.029***	0.067***	0.101***	0.115***	0.056***	0.090***	0.125***	0.132***
	(0.008)	(0.011)	(0.014)	(0.017)	(0.008)	(0.011)	(0.013)	(0.016)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,820	62,822	62,823	62,824	65,273	65,273	65,273	65,273

Panel B: News with an initial negative market reaction.								
	Alternative measure of *Negative news*				Excluding overlapping news			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+65)	(0,+107)	(0,+149)	(0,+212)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Contrarian_rank	0.028***	0.024***	0.022***	0.021***	0.023***	0.020***	0.018***	0.017***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)
Market Cap.	0.019***	0.021***	0.015*	–0.004	0.021***	0.024***	0.019***	–0.003
	(0.004)	(0.006)	(0.008)	(0.009)	(0.003)	(0.005)	(0.006)	(0.007)
ROA	0.180**	0.299***	0.355***	0.344***	0.191***	0.288***	0.330***	0.299***
	(0.073)	(0.082)	(0.103)	(0.117)	(0.070)	(0.077)	(0.092)	(0.112)
Tobin's Q	0.001***	0.002***	0.002***	0.002***	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	–0.082***	–0.048***	–0.016	0.018	–0.087***	–0.055***	–0.024**	0.009
	(0.007)	(0.010)	(0.013)	(0.016)	(0.006)	(0.008)	(0.011)	(0.014)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,587	64,587	64,587	64,587	65,904	65,904	65,904	65,904

Table 7. Stock price reactions to news announcements: cross-section according to news type

This table presents OLS regressions examining how the relation between stock returns and contrarian recommendations vary in the cross-section of news. We partition news into *Soft* and *Hard* type. News that are classified neither as hard neither as soft information are removed from the estimation sample. The dependent variable is the *H*-day buy-and-hold abnormal returns of the stock return over the daily C/R/S/P value-weighted return. We present the results separately for *Positive* (Panel A) and *Negative* news (Panel B). Control variables include *Market Capitalization*, *Return on Assets*, and *Market-to-Book*. Each time a control variable is introduced it is also interacted with the *Soft vs.* Hard dummy. Standard errors are adjusted for heteroskedasticity and clustered by stocks. They are displayed below the coefficient estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: News with an initial positive market reaction.								
	Dependent variable: buy-and-hold abnormal return over different windows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+65)	(0,+107)	(0,+149)	(0,+212)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Contrarian_rank	–0.028***	–0.027***	–0.027***	–0.032***	–0.028***	–0.027***	–0.028***	–0.033***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Soft vs. Hard	–0.057***	–0.056***	–0.055***	–0.050***	–0.058***	–0.056***	–0.054***	–0.047***
	(0.006)	(0.008)	(0.009)	(0.012)	(0.006)	(0.008)	(0.010)	(0.012)
Soft x Contr.	–0.010***	–0.008**	–0.010**	–0.007	–0.010***	–0.008**	–0.009**	–0.006
	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)
Controls (inter.)	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,257	56,258	56,259	56,259	56,172	56,173	56,174	56,174

Panel B: News with an initial negative market reaction.								
	Dependent variable: buy-and-hold abnormal return over different windows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+65)	(0,+107)	(0,+149)	(0,+212)	(0,+65)	(0,+107)	(0,+149)	(0,+212)
Contrarian_rank	0.031***	0.030***	0.033***	0.036***	0.028***	0.027***	0.029***	0.032***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Soft vs. Hard	0.028***	0.027***	0.036***	0.048***	0.028***	0.026***	0.034***	0.046***
	(0.005)	(0.007)	(0.008)	(0.010)	(0.005)	(0.007)	(0.008)	(0.010)
Soft x Contr.	0.004**	0.004	–0.000	–0.005	0.005***	0.005*	0.001	–0.004
	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)
Controls (inter.)	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,234	57,234	57,234	57,234	57,155	57,155	57,155	57,155

heterogeneity among analysts in how frequently they revise their recommendations results in recommendations following public news to be spread over several months. This delay in information processing has long-term effects on stock prices: stocks with a low level of contrarian recommendations tend to drift in the direction of the initial surprise, while stocks with a high level of contrarian recommendations tend to exhibit return reversal. Together, our results support the idea that analysts provide value to investors through their interpretation role and that their recommendations have long-term real effects on stock prices.

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