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Stock Return Dynamics after Analyst Recommendation Revisions

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Abstract

The study explores the correlation between the immediate and the longer-term stock returns following analyst recommendation revisions. In line with previous studies, documenting that recommendation revisions are followed by significant stock price drifts , I suggest that if a recommendation revision is followed by a relatively large short-term stock price drift, then it may indicate that the new information is more completely reflected by the respective stock's price, creating significantly less reasons for subsequent longer-term price drift, which therefore, should be significantly less pronounced compared to the one following another recommendation revision which is not immediately followed by a significant price drift in a short run. Employing a sample of recommendation revisions, I establish that positive (negative) one-, three- and six-month stock price drifts after recommendation upgrades (downgrades) are significantly more pronounced if the latter are immediately followed by relatively low (high) short-term (5- or 10-day) cumulative abnormal returns. The effect remains robust after accounting for additional company-specific (size, Market-Model beta, historical volatility) and event-specific (number of recommendation categories changed in the revision, analyst experience) factors.

JEL Classification numbers: G11, G14, G19
Keywords: Analyst Recommendation Revisions; Behavioral Finance; Overreaction; Stock Price Drifts.

1 Introduction

This paper focuses on the correlation between the immediate and the longer-term stock returns after analyst recommendation revisions. Numerous previous studies comprehensively analyze the ways analyst recommendations affect stock prices, concluding that the former contain important investment information (e.g., Green, 2006; Sorescu and Subrahmanyam, 2006; Loh and Stulz, 2011; Li et al., 2015). Additionally, the literature documents that recommendation revisions are more informative than the recommendation levels (e.g., Francis and Soffer, 1997; Jegadeesh and Kim, 2010) and lead to significant excess stock returns, whose sign corresponds to the direction of the revision.

Another influential aspect of stock price reactions to recommendation revisions is related to systematic price drifts taking place after the initial revisions (e.g., Womack, 1996; Nagel, 2005). These drifts may last up to one month after recommendation upgrades and up to six months after recommendation downgrades.

The existence of post-recommendation price drifts is quite intriguing, since it implies that the information is not fully incorporated in a stock's price at the moment when a recommendation revision with respect to the stock is released. This result looks possible, but contradicts the widely accepted semi-strong form of market efficiency. The existence of post-recommendation price drifts is usually

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explained by investor inattention to public information released by companies leading to underreaction to news (e.g., Hirshleifer et al., 2011; Peng and Xiong, 2006). Various empirical indicators are used as proxies for investor inattention, including, for example, days of the week (DellaVigna and Pollet, 2009), daily share turnover (Hou et al., 2009), days with abnormal Google search activity (Drake et al., 2012) high news days (Hirshleifer et al., 2009), and front-page articles about the stock market (Yuan, 2015).

In this study, I strive to analyze additional aspects of post-recommendation price drift dynamics. Namely, I suggest that if a recommendation revision is followed by a relatively large stock price drift during a short period after the revision, then it may indicate that the new information is more completely reflected by the stock price, creating significantly less reasons for subsequent longer-term price drift, which therefore, should be significantly less pronounced compared to the one following another recommendation revision which is not immediately followed by a price drift in the short run.

Using a large database of recommendations revisions, I document a series of results corroborating the study's hypothesis. I find that one-, three- and six-month positive price drifts after recommendation upgrades are significantly more pronounced if the latter are followed by relatively low (lowest sample quintile or decile) short-term (5- or 10-day) cumulative abnormal returns. Symmetrically, I detect that one-, three- and six-month negative price drifts after recommendation downgrades are significantly more pronounced if the latter are followed by relatively high (highest sample quintile or decile) short-term (5- or 10-day) cumulative abnormal returns. In other words, the results may imply that if for some reasons, investors produce a weak "initial" price drift, or even price reversal, following a recommendation revision, then there may be a less complete reaction, or even underreaction, to news, so that during the subsequent period, the respective stock's price is less likely to drift in the direction of the initial recommendation revision. The documented effect of post-recommendation price drifts on subsequent stock price dynamics remains robust after accounting for additional company-specific (size, Market-Model beta, historical volatility) and event-specific (number of recommendation categories changed in the revision, analyst experience) factors.

The rest of the paper is structured as follows. Section 2 briefly reviews the literature dealing with recommendation revisions and subsequent stock price drifts. Section 3 introduces the study's research hypothesis. Section 4 presents the database and the research design. Section 5 reports the empirical tests and the results. Section 6 concludes and provides a brief discussion.

2 Literature review

Information plays a crucial role in modern financial markets, and in this respect, financial analysts serve as an important information intermediaries (e.g., Lang and Lundholm, 1996; Healy and Palepu, 2001; Beyer et al., 2010). The analysts' activity may improve efficiency of the market, since their recommendations, representing their expert opinions about specific stocks, are expected to provide previously unknown information (e.g., Grossman, 1995; Frankel et al., 2006). Recommendation revisions, defined as the differences between analysts' current recommendations and their previous ones regarding the same stocks (Boni and Womack, 2006), are in the focus of a large body of financial literature and are documented to be more informative than the recommendation levels regarding the subsequent stock price reactions (e.g., Francis and Soffer, 1997; Jegadeesh et al., 2004; Jegadeesh and Kim, 2010).

Previous literature dealing with analyst recommendation revisions generally concludes that the latter contain useful investment information for investors. Stickel (1995) argues that recommendation revisions issued by brokerage houses affect stock prices. He finds that short-term price reaction is a function of the strength of the recommendation; the size of the recommended firm; the contemporaneous earnings forecast revisions; the magnitude of the change in recommendation; the reputation of the analyst; and the size of the brokerage house. The first three factors represent information effects and are associated with permanent price changes, while the last three ones refer to temporary, price pressure effects. Womack (1996) analyzes revisited buy and sell recommendations of stocks by security analysts at major U.S. brokerage firms and documents significant, systematic differences between pre-recommendation and post-recommendation prices. Recommendation revisions, especially recommendation downgrades, are accompanied by economically and statistically significant returns, even though few recommendations coincide with new public news or provide previously unavailable facts. Green (2006) demonstrates that early access to stock recommendations provides brokerage firm clients with incremental investment value. After controlling for transaction costs, purchasing (selling short) after upgrades (downgrades) results in significantly positive two-day returns.

A wide strand of literature concentrates on the reasons for differential stock price reactions to analyst recommendations and recommendation revisions. Mikhail et al. (2004) investigate whether security analysts are consistent in their stock picking abilities, and detect that analysts whose recommendation revisions earned the highest (lowest) excess returns in the past continue to outperform (underperform) in the future. Loh and Mian (2006) find that analysts who possess more accurate earnings forecasts at the time of the recommendation issue more profitable stock recommendations. Sorescu and Subrahmanyam (2006) demonstrate that low strength recommendation changes by analysts from reputable brokerages are associated with more return persistence. Similarly, Loh and Stulz (2011) show that a recommendation is more likely to generate a sizable stock reaction if it is issued by a leading analyst. Michaely and Womack (2006) and Kecskes et al. (2010) document that stock recommendations accompanied by the same-direction earnings forecast revisions result in higher stock price reactions and are more profitable. Jegadeesh and Kim (2010) suggest that recommendations that move away from consensus cast stronger effects on stock prices. Li et al. (2015) argue that analyst recommendations play an important role in generating the momentum effect.

Various studies report incomplete reactions to analyst recommendations leading to predictable price drifts (e.g., Elton et al., 1986; Brav and Lehavy, 2003; Gleason and Lee, 2003). These price drifts tend to last up to one month for recommendation upgrades and up to six months for recommendation downgrades (e.g., Womack, 1996; Barber et al., 2001). It should be noted that though immediate price reactions to stock recommendations are consistent with the notion of efficient capital markets, predictable post-recommendation price drifts contradict the prevailing theory of semi-strong form of market efficiency by Malkiel and Fama (1970), which states that investors should not be able to gain profits based on the publicly available information, including analyst recommendations.

Post-recommendation price drifts may differ in their magnitude for different types of recommendations and different groups of stocks. Womack (1996) documents that the drifts following the sell recommendations are larger and more long-lived than those following the buy recommendations. Barber et al. (2001) establish that smaller companies' stocks are characterized by more significant price drifts. Stickel (1995) finds that recommendation revisions by larger brokerage houses are followed by larger subsequent price drifts.

Existence of systematic and significant post-recommendation price drifts raises the question as to why the information is not fully incorporated in the stock price right at the moment when the recommendation is released. One potential reason refers to short-sale constraints (e.g., Diether et al., 2002; Nagel, 2005) that may lead to negative drifts after downgrades, but cannot explain underreaction to upgrades. Barber et al. (2001) propose an explanation that markets are not efficient in the semi-strong form, suggesting that stock returns may be predictable based on public information, like stock recommendations.

Yet the most popular explanation for the existence of the post-recommendation price drifts stems from investors' inattention. Theoretical models predict that the latter may cause underreaction to public information, in general. Hirshleifer et al. (2011) construct a model where some of the investors neglect the information about the firm's future profitability contained in an earnings surprise, and conclude that this should lead to the firm's stock price underreaction to announcements of earnings surprises. Peng and Xiong (2006) present a model where investor attention constraints result in "category learning", when investors focus more on market-wide and industry-wide rather than on firm-specific information. This implies that investors could underreact to firm-specific information such as analysts' stock recommendations.

Another wide group of empirical studies confirm the above-mentioned models' predictions, using different proxies for investor inattention and analyzing various types of company-specific news. Chen et al. (2004) detect asymmetric price effects of the recommendation revisions around stock additions to and deletions from the S&P500 index, and attribute the differences to increased attention to a stock that becomes a part of the index. In the same spirit, DellaVigna and Pollet (2009) show that the stock price reactions to earnings announcements on Fridays are weaker than on other week-days. The result may be attributed to the fact that investors may be distracted by the upcoming weekend. Hong et al. (2007) document that a number of industry returns can forecast the market's return by up to two months and argue that investors are inattentive to the predictive information contained in industry returns. Similarly, Cohen and Frazzini (2008) reveal abnormal profits to a strategy of buying (selling) stocks of the firms whose customers experience positive (negative) news and conclude that investors are inattentive to customer linkages between firms. Hou et al. (2009) employ share turnover as a proxy for investor attention and demonstrate that an earnings momentum strategy is more profitable when investors are inattentive. Hirshleifer et al. (2009) use high-news days (days when numerous earnings announcements are issued) as a proxy for investor inattention and report weaker reactions to earnings announcements on such days. Drake et al. (2012) provide evidence that abnormal Google search activity in the days before the earnings announcement is associated with decreased price reactions to the latter. Yuan (2015) demonstrates that attention-grabbing events, such as record levels for the Dow Jones Index and front-page articles about the stock market, can serve as predictors of future stock market returns, especially when the market index level is already high.

Several studies focus on the effect of investor inattention on stock price reactions to analyst recommendation revisions and on subsequent price drifts. Loh (2010) uses different proxies for investor inattention, namely the prior stock turnover, the number of simultaneously published earnings announcements, indicating how distracted investors may be, and also the percentage of institutional ownership and the number of analysts covering the stock, reflecting the number of sophisticated investors who pay attention to the firm. He empirically establishes that investors tend to underreact to news about firms that are not attention grabbing. Respectively, if investors temporarily neglect the information contained in stock recommendations, then predictable price drifts should follows when they gradually incorporate this information. Gavriilidis et al. (2016) continue Loh's (2010) line of reasoning, but concentrate on attention grabbing recommendations, proxied by abnormally high event-day trading volumes, rather than on attention grabbing firms. They conclude that recommendations that are accompanied by high attention are followed by consistently more pronounced post-announcement drifts than otherwise similar recommendations. They also show that this effect is more pronounced for upgrades than for downgrades.

3 Research hypothesis

As shown in the previous Section, financial literature concludes that analyst recommendation revisions are followed by systematic and significant post-recommendation price drifts. The main goal of this study is to shed more light on the dynamics of these drifts.

Namely, I hypothesize that if a recommendation revision is followed by a relatively large stock price drift during a short period after the revision, then it may indicate that the new information is more completely incorporated in the stock price, leaving significantly less space for subsequent longer-term price drift. In other words, I expect that if for some reasons, investors produce a strong "initial" price drift following a recommendation revision, then there is a more complete reaction, or even overreaction, to news, so that during the subsequent period, the respective stock's price will be less likely to drift in the direction of the recommendation revision, and may even experience a reversal.

Thus, the study's major research hypothesis deals with the effect of the initial post-recommendation price drifts on the subsequent stock price dynamics, and may be formulated as follows:

Hypothesis: *If a recommendation upgrade (downgrade) is immediately followed by relatively high (low) abnormal short-term stock returns, then the stock's cumulative abnormal returns during the subsequent longer-term periods should be lower (higher).*

4 Data description and research design

I collect the sample of stock recommendations from the Thomson Financials I/B/E/S database for the period from 2003 to 2017. I/B/E/S stock recommendations are coded in integers from 1 (for Strong Buy) to 5 (for Strong Sell). I focus on recommendation revisions, that is, on the differences between the current and the most recent recommendation levels, since prior research confirms that recommendations changes are more informative than mere levels (e.g., Boni and Womack, 2006; Jegadeesh and Kim, 2010). I define the day of a recommendation revision as the event day (Day 0), except when a revision falls on a non-trading day. In the latter case, the event day is defined as the trading day following the day the recommendation was updated.

Similarly to Li et al. (2016), I exclude from the sample recommendation initiations (first-time recommendations of an analyst on a stock) and re-initiations (new recommendations issued by an analyst on a stock after more than a year from her previous recommendation on the same stock). Furthermore, following Loh (2010) and in order to be sure that a stock price's reaction to a recommendation revision was not partially driven by a contemporaneous earnings announcement of the same company, I remove from the sample recommendation revisions that had been issued in the three-day window centered around the I/B/E/S quarterly earnings announcement dates. Finally, I drop the stocks with share prices below $1.00.

I merge the I/B/E/S recommendations data with daily stock price data for all NYSE, AMEX and NASDAQ common stocks from the Center for Research in Security Prices (CRSP)[2]. In addition, for each recommendation revision, I match the respective company's market capitalization, as recorded on a quarterly basis at http://ycharts.com/, for the closest preceding announcement date.

Table 1 depicts basic descriptive statistics for the companies undergoing stock recommendation revisions and for the analysts being involved. The statistics include companies' market capitalization for the closest preceding announcement date; Market Model beta estimated over days -251 to -1 (roughly one year) preceding the event day (the day when the recommendation revision was released), with S&P 500 Index employed as a proxy for the market portfolio; standard deviation of daily stock returns over the same period; and analyst experience proxied by the number of years that the analyst exists in I/B/E/S prior to the specific recommendation revision. The sample consists of 77,894 (87,342) recommendation upgrades (downgrades). Mean market capitalization equals 4,654 (4,497) millions of dollars, mean beta is 1.03 (1.12), mean historical volatility of stock returns equals 1.75 (1.80) percent, and the mean analyst experience is 5.70 (5.59) years. So, overall, there seem to be no fundamental differences in the descriptive statistics for the recommendation upgrades and downgrades.

Table 2 classifies the analyst recommendation revisions in the sample by recommendation categories before the revision (Panel A), by the number of categories changed in the revision (Panel B), and by calendar years (Panel C). For the vast majority of analyst recommendation revisions in the sample only one rating category is changed, and the distribution of the revisions by years is quite homogeneous. Once again, the distribution characteristics of the recommendation upgrades and downgrades look quite similar.

5 Results description

5.1. Stock price dynamics following recommendation revisions: Total sample

In order to measure stock price dynamics following recommendation revisions, I calculate daily abnormal stock returns (ARs) using Market Model Adjusted Returns (MMAR)[3]. That is, for each event (recommendation revision) *i*, for days -251 to -1 preceding the event, I regress the respective stock's returns on the contemporaneous market (S&P 500 Index) returns in the following way:

[2] The two data sets are merged based on either CUSIP or exchange tickers combined with the requirement that the period these identifiers are used in the data sets overlap.

[3] Alternatively, I calculate ARs using Market Adjusted Returns (MAR) – return differences from the market index, and the Fama-French three-factor model. The results (available upon request from the author) remain qualitatively similar to those reported in Section 5.

$$SR_{it} = \alpha_i + \beta_i MR_{it} + \varepsilon_{it} \quad (1)$$

where: *SRit* is the stock return on day *t* (*t* runs from -251 to -1) preceding event *i*; and *MRit* is the market return on day *t* preceding event *i*, and then use the regression estimates $\widehat{\propto_i}$ and $\widehat{\beta_i}$ in order to calculate ARs for each of 126 days following event *i*, as follows:

$$AR_{it} = SR_{it} - [\widehat{\propto_i} + \widehat{\beta_i} MR_{it}] \quad (2)$$

where: *ARit* is the abnormal stock return on day *t* following event *i* (*t* runs from 0 to 126); and *SRit* and *MRit* represent the stock and the market returns for the respective days following event *i*.

For estimating the post-recommendation stock price dynamics, I employ cumulative ARs (CARs) for Days 1 to 21, Days 1 to 63 and Days 1 to 126, roughly corresponding to one month, three months and six months after the revision, respectively[4].

Table 3 presents CARs for the three above-mentioned post-event periods following recommendation upgrades and downgrades, and their statistical significance. The results indicate the existence of significant price drifts following both upgrades and downgrades, and are also consistent with previous literature (e.g., Womack, 1996; Barber et al., 2001), in the meaning that the magnitude of the drifts following recommendation upgrades gradually decreases after the first post-event month, while the magnitude of the drifts following recommendation downgrades increases during the whole analyzed six-month post-event period.

5.2. The effect of post-recommendation price drifts on subsequent stock price dynamics

In order to test the study's hypothesis, I classify the recommendation revisions included in the sample in accordance with the magnitude of the short-term post-recommendation abnormal returns. Table 4 reports CARs for Days 6 to 21, Days 6 to 63 and Days 6 to 126 following recommendation upgrades and downgrades separately for the highest and the lowest 5-day post-event CAR quintiles and deciles, and the respective CAR differences. Table 5 does the same thing based on 10-day post-event CAR classification. The results corroborate the existence of the effect of post-recommendation price drifts on subsequent stock price dynamics, indicating that:

- For recommendation upgrades immediately followed by the highest-quintile or decile 5- or 10-day CARs, that is, by the most pronounced immediate price drifts, there are significantly negative average CARs over all the subsequent periods. On the other hand, stocks whose 5- or 10-day CARs following recommendation upgrades are in the lowest quintile or decile, subsequently experience significantly positive average CARs whose magnitude gradually increases for longer post-event windows. For example, average CAR for days 6 to 126 after recommendation upgrades immediately followed by the lowest-decile 5-day CARs reaches a non-negligible figure of 1.51%.
- For recommendation downgrades immediately followed by the lowest-quintile or decile 5- or 10-day CARs, that is, by the most pronounced immediate price drifts, there are significantly positive average CARs over all the subsequent periods. On the other hand, stocks whose 5- or 10-day CARs following recommendation downgrades are in the highest quintile or decile, subsequently experience significantly negative average CARs whose magnitude gradually increases for longer post-event windows. For example, average CAR for days 6 to 126 after recommendation downgrades immediately followed by the highest-decile 5-day CARs is -1.62%.
- For both recommendation upgrades and downgrades, average CAR differences between the revisions immediately followed by the highest- and the lowest-quintile or decile 5- or 10-day CARs, are highly significant, and their magnitude gradually increases for longer post-event windows. For example, for post-event days 6 to 126, average CAR differences between recommendation upgrades (downgrades) followed by the highest- and the lowest-decile 5-day CARs is -1.94% (-2.08%). This result implies that subsequent positive (negative) price drifts are significantly more pronounced for recommendation upgrades (downgrades) immediately followed by relatively low (high) CARs.

[4] I choose to analyze post-recommendation periods of one, three and six months following, for example, Loh (2010) and Gavriilidis et al. (2016).

5.3. Multifactor analysis

Having detected the effect of post-recommendation price drifts on subsequent stock price dynamics, I check its persistence, controlling for additional company-specific and event-specific factors. To do so, separately for recommendation upgrades and downgrades, I run the following regressions for post-event days 6 (or 11) to 21, 6 (or 11) to 63 and 6 (or 11) to 126:

$$CAR_{it} = \beta_0 + \beta_1 Immediate\_High_i + \beta_2 Immediate\_Low_i + \beta_3 MCap_i + \beta_4 Beta_i + +\beta_5 SRVolat_i + \beta_6 Magnitude_i + \beta_7 Experience_i + \varepsilon_{it} \quad (3)$$

where: *CARit* is the cumulative abnormal stock return following event *i* for the post-event window *t* (Days 6 (or 11) to 21, 6 (or 11) to 63 or 6 (or 11) to 126); *Immediate_Highi* is the dummy variable, taking the value 1 if the 5- or 10-day CAR following event *i* is in the highest sample quintile, and 0 otherwise; *Immediate_Lowi* is the dummy variable, taking the value 1 if the 5- or 10-day CAR following event *i* is in the lowest sample quintile, and 0 otherwise[5]; *MCapi* is the natural logarithm of the firm's market capitalization corresponding to event *i*, normalized in the cross-section; *Betai* is the estimated Market Model beta for event *i*, calculated over the Days -251 to -1 and normalized in the cross-section; *SRVolati* is the standard deviation of stock returns over the Days -251 to -1 corresponding to event *i*, normalized in the cross-section; *Magnitudei* is the number of categories changed in the revision; and *Experiencei* is the natural logarithm of number of years that the analyst providing recommendation revision *i* exists in I/B/E/S prior to the revision, normalized in the cross-section.

Tables 6 and 7 comprise regression coefficient estimates for all the post-event windows, with 5- and 10-day periods, respectively, employed for measuring the initial post-event stock price moves. The results show that:

- In the case of the recommendation upgrades, for all the post-event windows, regression coefficients on *Immediate_High* are significantly negative and regression coefficients on *Immediate_Low* are significantly positive, suggesting once again that positive longer-term price drifts after recommendation upgrades are significantly less (more) pronounced if the latter are immediately followed by relatively high (low) short-term CARs.
- Similarly, in the case of the recommendation downgrades, for all the post-event windows, regression coefficients on *Immediate_High* are significantly negative and regression coefficients on *Immediate_Low* are significantly positive, suggesting that negative longer-term price drifts after recommendation downgrades are significantly more (less) pronounced if the latter are immediately followed by relatively high (low) short-term CARs.
- For all the post-event windows following recommendation upgrades (downgrades), the regression coefficients on *MCap* are significantly negative (positive), the regression coefficients on *Beta* are positive (negative) and marginally significant, and the regression coefficients on *SRVolat* are significantly positive (negative), indicating that post-event CARs following recommendation upgrades (downgrades) tend to be higher (lower) for low capitalization, high-beta and highly volatile stocks. A potential reason for these findings may be that investors possess less fundamental information on these groups of stocks and therefore, tend to react stronger to salient company-specific events. It should be noted again that the effect of post-recommendation price drifts on subsequent stock price dynamics remains significant after controlling for the above-mentioned factors.
- For all the post-event windows following recommendation upgrades (downgrades), the regression coefficients on *Magnitude* and *Experience* are positive (negative) and marginally significant, demonstrating that stock price reactions to recommendation revisions tend to be stronger the greater the number of recommendation categories changed in the revision and the more experienced is the analyst providing the revision.

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[5] I have repeated the regression analysis defining *Immediate_Highi* and *Immediate_Lowi* variables for the highest and the lowest CAR deciles, rather than quintiles. The results (available upon request from the author) remain qualitatively similar to those reported in Subsection 5.3.

6 Concluding remarks

In this study, I explored the correlation between the immediate and the longer-term stock price reactions to analyst recommendation revisions. Following the previous literature, which documented significant stock price drifts after recommendation revisions, I suggested that if a recommendation revision is followed by a relatively large stock price drift during a short period after the revision, then it may indicate that the new information is more completely incorporated in the stock price, leaving significantly less space for subsequent longer-term price drift, which therefore, should be significantly less pronounced compared to another recommendation revision which is not immediately followed by a short-term price drift.

The results of the empirical analysis supported the study's hypothesis. Analyzing a large sample of analyst recommendation revisions, I established that positive (negative) longer-term stock price drifts after recommendation upgrades (downgrades) are significantly more pronounced if the latter are immediately followed by relatively low (high) short-term cumulative abnormal returns. The effect remained significant after accounting for additional company-specific (size, Market Model beta, historical volatility) and event-specific (number of recommendation categories changed in the revision, analyst experience) factors. The results proved to be robust to different methods of adjusting returns, such as market-adjusted returns, market-model excess returns, and Fama-French three-factor model excess returns.

To summarize, at least in a perfect stock market with no commissions, the strategy based on buying (selling short) stocks that have undergone recommendation upgrades (downgrades) followed by relatively low (high) short-term cumulative abnormal returns, looks promising. This may prove a valuable result for both financial theoreticians in their eternal discussion about stock market efficiency, and practitioners in search of potentially profitable investment strategies. Potential directions for further research may include performing a separate analysis for high and low market capitalization stocks and for the periods of bull and bear market.

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Appendix (Tables)

Table 1: Descriptive statistics for the firms making up the sample and the stock analysts

Category of recommendation revisions	Number of recommendation revisions	Market capitalization, $ millions		Market Model Beta		St. Dev. of historical stock returns, percent		Analyst experience, years	
		Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Upgrades	77,894	4,654	12,235	1.03	0.35	1.75	0.82	5.70	2.53
Downgrades	87,342	4,497	12,140	1.12	0.37	1.80	0.85	5.59	2.54
Total	*165,236*	*4,578*	*11,672*	*1.08*	*0.34*	*1.78*	*0.84*	*5.64*	*2.51*

Table 2: Descriptive statistics of the recommendation revisions in the sample

Panel A: Recommendation revisions by categories before revision			
Category before revision	Number of recommendation revisions		
	Upgrades	Downgrades	Total
1	0	14,826	14,826
2	4,659	46,312	50,971
3	42,829	22,394	65,223
4	29,226	3,810	33,036
5	1,180	0	1,180
Total	*77,894*	*87,342*	*165,236*
Panel B: Recommendation revisions by number of categories changed in the revision			
Number of categories changed in the revision	Number of recommendation revisions		
	Upgrades	Downgrades	Total
1	72,023	80,469	152,492
2	5,552	6,485	12,037
3	256	298	554
4	63	90	153
Total	*77,894*	*87,342*	*165,236*
Panel C: Recommendation revisions by calendar years			
Year	Number of recommendation revisions		
	Upgrades	Downgrades	Total
2003	4,995	5,849	10,844
2004	5,225	5,710	10,935
2005	5,197	5,644	10,841
2006	5,278	6,025	11,303
2007	5,091	5,807	10,898
2008	5,181	5,770	10,951
2009	5,282	5,785	11,067
2010	5,086	5,821	10,907
2011	5,244	5,896	11,140
2012	5,198	5,743	10,941
2013	5,041	5,793	10,834
2014	5,308	5,944	11,252
2015	5,240	5,739	10,979
2016	5,202	5,867	11,069
2017	5,326	5,949	11,185
Total	*77,894*	*87,342*	*165,236*

Table 3: Stock price dynamics following recommendation revisions: Total sample

Days relative to event	Average CARs following recommendation revisions, % (2-tailed p-values)	
	Upgrades	Downgrades
1 to 21	***0.42 (0.21%)	***-0.49 (0.11%)
1 to 63	***0.41 (0.19%)	***-0.61 (0.00%)
1 to 126	***0.35 (0.15%)	***-0.94 (0.00%)

Asterisks denote 2-tailed p-values: ****p*<0.01

Table 4: Stock price dynamics following recommendation revisions as a function of 5-day post-event price moves

Panel A: Recommendation upgrades						
Days relative to event	Average CARs following post-event price moves, % (2-tailed p-values)					
	5-day post-event CAR quintile			5-day post-event CAR decile		
	Highest	Lowest	Difference	Highest	Lowest	Difference
6 to 21	**-0.19 (1.24%)	***0.92 (0.06%)	***-1.11 (0.02%)	**-0.21 (1.10%)	***0.98 (0.04%)	***-1.19 (0.00%)
6 to 63	***-0.30 (0.31%)	***1.11 (0.00%)	***-1.41 (0.00%)	***-0.34 (0.29%)	***1.20 (0.00%)	***-1.54 (0.00%)
6 to 126	***-0.38 (0.14%)	***1.37 (0.00%)	***-1.75 (0.00%)	***-0.43 (0.09%)	***1.51 (0.00%)	***-1.94 (0.00%)
Panel B: Recommendation downgrades						
Days relative to event	Average CARs following post-event price moves, % (2-tailed p-values)					
	5-day post-event CAR quintile			5-day post-event CAR decile		
	Highest	Lowest	Difference	Highest	Lowest	Difference
6 to 21	***-0.95 (0.02%)	***0.23 (0.87%)	***-1.18 (0.00%)	***-0.99 (0.00%)	***0.25 (0.77%)	***-1.24 (0.00%)
6 to 63	***-1.28 (0.00%)	***0.34 (0.21%)	***-1.62 (0.00%)	***-1.37 (0.00%)	***0.37 (0.14%)	***-1.74 (0.00%)
6 to 126	***-1.47 (0.00%)	***0.42 (0.10%)	***-1.89 (0.00%)	***-1.62 (0.00%)	***0.46 (0.07%)	***-2.08 (0.00%)

Asterisks denote 2-tailed p-values: ***p*<0.05; ****p*<0.01

Table 5: Stock price dynamics following recommendation revisions as a function of 10-day post-event price moves

Panel A: Recommendation upgrades						
Days relative to event	Average CARs following post-event price moves, % (2-tailed p-values)					
	10-day post-event CAR quintile			10-day post-event CAR decile		
	Highest	Lowest	Difference	Highest	Lowest	Difference
11 to 21	**-0.15 (1.48%)	***0.79 (0.15%)	***-0.94 (0.08%)	**-0.16 (1.35%)	***0.83 (0.07%)	***-0.99 (0.03%)
11 to 63	***-0.26 (0.39%)	***0.98 (0.03%)	***-1.24 (0.00%)	***-0.29 (0.40%)	***1.05 (0.00%)	***-1.34 (0.00%)
11 to 126	***-0.34 (0.18%)	***1.24 (0.00%)	***-1.58 (0.00%)	***-0.38 (0.14%)	***1.36 (0.00%)	***-1.74 (0.00%)
Panel B: Recommendation downgrades						
Days relative to event	Average CARs following post-event price moves, % (2-tailed p-values)					
	10-day post-event CAR quintile			10-day post-event CAR decile		
	Highest	Lowest	Difference	Highest	Lowest	Difference
11 to 21	***-0.81 (0.06%)	**0.18 (1.03%)	***-0.97 (0.04%)	***-0.83 (0.04%)	***0.20 (0.94%)	***-1.03 (0.00%)
11 to 63	***-1.14 (0.00%)	***0.29 (0.28%)	***-1.43 (0.00%)	***-1.21 (0.00%)	***0.32 (0.21%)	***-1.53 (0.00%)
11 to 126	***-1.33 (0.00%)	***0.37 (0.13%)	***-1.70 (0.00%)	***-1.46 (0.00%)	***0.45 (0.11%)	***-1.91 (0.00%)

Asterisks denote 2-tailed p-values: **p<0.05; ***p<0.01

Table 6: Multifactor regression analysis of stock price dynamics following recommendation revisions as a function of 5-day post-event price moves: Dependent variables – Stock CARs for different post-event windows

Panel A: Recommendation upgrades			
Explanatory variables	Coefficient estimates, % (2-tailed p-values)		
	CAR (6, 21)	CAR (6, 63)	CAR (6, 126)
Intercept	***0.22 (0.51%)	***0.23 (0.57%)	***0.18 (0.87%)
Immediate_High	***-0.70 (0.00%)	***-0.82 (0.00%)	***-0.84 (0.00%)
Immediate_Low	***0.42 (0.05%)	***0.59 (0.00%)	***0.91 (0.00%)
MCap	**-0.16 (1.32%)	***-0.23 (0.67%)	***-0.26 (0.51%)
Beta	0.07 (13.25%)	0.08 (12.68%)	*0.09 (9.87%)
SRVolat	**0.14 (3.01%)	**0.15 (2.76%)	**0.16 (2.10%)
Magnitude	*0.08 (7.24%)	*0.09 (6.85%)	**0.11 (4.84%)
Experience	*0.07 (7.86%)	*0.08 (6.44%)	*0.08 (6.47%)
Panel B: Recommendation downgrades			
Explanatory variables	Coefficient estimates, % (2-tailed p-values)		
	CAR (6, 21)	CAR (6, 63)	CAR (6, 126)
Intercept	***-0.33 (0.41%)	***-0.45 (0.14%)	***-0.66 (0.08%)
Immediate_High	***-0.63 (0.00%)	***-0.54 (0.02%)	***-0.85 (0.00%)
Immediate_Low	***0.54 (0.02%)	***0.80 (0.00%)	***1.01 (0.00%)
MCap	**0.26 (2.11%)	**0.27 (1.98%)	***0.30 (0.78%)
Beta	-0.06 (13.64%)	-0.05 (15.24%)	-0.07 (10.55%)
SRVolat	**-0.17 (2.67%)	**-0.18 (2.31%)	**-0.20 (1.64%)
Magnitude	*-0.09 (6.31%)	*-0.08 (7.58%)	**-0.11 (4.72%)
Experience	*-0.06 (7.14%)	*-0.07 (6.77%)	*-0.08 (5.89%)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.0

Table 7: Multifactor regression analysis of stock price dynamics following recommendation revisions as a function of 10-day post-event price moves: Dependent variables – Stock CARs for different post-event windows

Panel A: Recommendation upgrades			
Explanatory variables	Coefficient estimates, % (2-tailed p-values)		
	CAR (11, 21)	CAR (11, 63)	CAR (11, 126)
Intercept	***0.23 (0.55%)	***0.21 (0.63%)	***0.17 (0.91%)
Immediate_High	***-0.61 (0.00%)	***-0.71 (0.00%)	***-0.74 (0.00%)
Immediate_Low	***0.38 (0.10%)	***0.54 (0.04%)	***0.75 (0.00%)
MCap	**-0.15 (1.68%)	***-0.22 (0.82%)	***-0.24 (0.63%)
Beta	0.07 (13.81%)	0.08 (13.05%)	0.08 (10.24%)
SRVolat	**0.12 (4.12%)	**0.13 (3.65%)	**0.15 (2.79%)
Magnitude	*0.07 (7.77%)	*0.08 (7.09%)	*0.10 (5.34%)
Experience	*0.06 (8.23%)	*0.07 (6.91%)	*0.08 (6.32%)
Panel B: Recommendation downgrades			
Explanatory variables	Coefficient estimates, % (2-tailed p-values)		
	CAR (11, 21)	CAR (11, 63)	CAR (11, 126)
Intercept	***-0.30 (0.48%)	***-0.42 (0.17%)	***-0.62 (0.07%)
Immediate_High	***-0.54 (0.03%)	***-0.47 (0.05%)	***-0.72 (0.00%)
Immediate_Low	***0.45 (0.11%)	***0.66 (0.00%)	***0.82 (0.00%)
MCap	**0.25 (2.23%)	**0.26 (2.07%)	***0.29 (0.92%)
Beta	-0.06 (14.03%)	-0.05 (15.39%)	-0.06 (12.84%)
SRVolat	**-0.15 (4.16%)	**-0.16 (3.60%)	**-0.18 (2.17%)
Magnitude	*-0.08 (6.82%)	*-0.07 (7.34%)	*-0.09 (5.29%)

Experience	*-0.05 (8.31%)	*-0.06 (7.15%)	*-0.07 (6.46%)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01