



On the investment value of sell-side analyst recommendation revisions in the UK

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Abstract

This study conducts a comprehensive investigation into the investment value of sell-side analyst recommendation revisions in the UK, using a unique dataset from 1995 to 2013. Our rolling window analysis shows that, on average, upgrades fail to generate any significantly positive abnormal returns in any period of time, even before transaction costs. In addition, although downgrades could generate significantly negative abnormal gross returns over some periods of time, these observed significant returns disappear after accounting for transaction costs. Overall, our bootstrapping simulations confirm sell-side analysts' lack of skill in making valuable up/downward revisions to cover the size of transaction costs, irrespective of whether these revisions are made by high-ranking brokerage houses or not. However, an industry-based analysis shows that, within two high-tech industry sectors, i.e., Health Care and Technology sectors, sell-side analysts possess certain skill in making valuable downgrades over some periods of time and, in particular, such skill is sufficient to offset transaction costs.

Keywords Analyst recommendation revisions · Transaction costs · High-ranking brokerage houses · Industry · Bootstrapping simulations

JEL Classification G11 · G12 · G14 · G17 · G24

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1 Introduction

Sell-side analysts working for brokerage houses play an important role in the capital markets by collecting and analyzing a variety of market, industry, and firm-specific information and then making stock recommendations.¹ These stock recommendations, disseminated through electronic and print media, have been widely used by investors in their investment decisions. Whether sell-side analyst recommendations can truly create investment value and promote market efficiency has been of great interest to financial academics. The related literature can stretch as back as the pioneering study of Cowles (1933), which shows that investors are not able to add value to the market when they follow analyst recommendations. The inability of financial analysts to predict stock price movements is confirmed by numerous following studies (see, e.g., Colker 1963; Logue and Tuttle 1973; Groth et al. 1979; among others), in spite of a substantial amount of money spent by brokerage houses on security analysis (Grossman and Stiglitz 1980).² In contrast, Stickel (1995) and Womack (1996) report that upgrades (downgrades)—favorable (unfavorable) changes in analyst recommendations—are accompanied by significantly positive (negative) returns at the time of their announcements. Barber et al. (2001) prove the existence of profitable investment strategies based on publicly available analyst recommendations, presenting a challenge to the semi-strong form of efficient market hypothesis (EMH). However, these investment strategies require a great deal of trading and generate considerable transaction costs, suggesting that the observed market inefficiencies are not easily exploitable by investors (see, also, Jegadeesh et al. 2004; Mikhail et al. 2004). Altinkiliç and Hansen (2009) further call into question the information role played by financial analysts in that their stock recommendation revisions often piggyback on public information (e.g., corporate events and news), thus providing investors with little incremental information (see, also, Altinkiliç et al. 2013).

Despite the existence of extensive sell-side analyst research in the US, empirical evidence on the investment value of analyst recommendations remains mixed. Jegadeesh and Kim (2006, p. 275) argue that an in-depth examination in other developed markets “will give us a more comprehensive picture of the extent to which the unique skill of analysts are useful for investors”. The UK stock market, a highly developed and sophisticated market, provides us with an appropriate setting to shed additional light on the existing controversy within this area of research, while it has received very scant attention in the financial literature. For example, Dimson and Fraletti (1986) examine an unpublished sample of 1649 telephone recommendations made by a leading UK brokerage house in 1983, but they find no significant abnormal returns for the recommended stocks. Ryan and Taffler (2006, p. 372) argue that the study of Dimson and Fraletti (1986) examines stock recommendations made by “a single UK brokerage house only and is biased towards large capitalization stocks”. Ryan and Taffler (2006) investigate a sample of 2506 changes in analyst recommendations

¹ Sell-side analysts typically work for brokerage houses (or investment banks) and make stock recommendations to investors in the capital markets, while buy-side analysts usually work for pension fund or mutual fund firms and make stock recommendations to money managers of the fund that employs them. This study focuses on stock recommendation revisions, exclusively made by sell-side analysts working for brokerage houses in the UK.

² Grossman and Stiglitz (1980) argue that if prices fully reflect all available information, then the use of analyst recommendations cannot generate superior returns, and brokerage houses should not spend large sums of money on security analysis, nor should market participants have any incentive to pay for such costly information.

made by six London-based brokerage houses from December 1993 to June 1995, showing that stock prices are significantly affected by analyst recommendation revisions.

Given the limited observations and short sample periods examined in prior UK studies, which generally suffer from small sample bias, this study aims to conduct a comprehensive investigation into a novel real-time database, uniquely created by *Morningstar Company Intelligence*. Our final sample consists of 70,220 analyst recommendation revisions for stocks either on the main market of the London Stock Exchange (LSE) or on the Alternative Investment Market (AIM) from January 1995 to June 2013; as such, our dataset is much larger than has been employed in prior UK studies. With the *Morningstar* database, we take an investor-oriented, calendar-time perspective,³ to assess the performance of investment strategies based on UK sell-side analyst recommendation revisions. Our study is close to Barber et al. (2001) and Barber et al. (2007), but differs from them in several major respects. For example, Barber et al. (2007) include initiations, resumptions, and reiterations when constructing their portfolios. However, sell-side analysts often leave their stock recommendations unchanged for long periods of time; as a result, these stock recommendations become stale and less informative over time (see, Jegadeesh et al. 2004; Boni and Womack 2006; Jegadeesh and Kim 2006, 2010). Therefore, unlike Barber et al. (2007), we construct two *upgrade* and *downgrade* portfolios by exclusively focusing on analyst recommendation revisions. Specifically, the *upgrade* portfolio includes all stocks with upward revisions to Strong Buys or Buys from previous Strong Sells, Sells, or Holds, while the *downgrade* portfolio includes all stocks with downward revisions to Strong Sells, Sells, or Holds from previous Strong Buys or Buys.

In addition, different from Barber et al. (2001) and Barber et al. (2007), we evaluate the performance of the *upgrade* and *downgrade* portfolios on a 1-year rolling window basis, using the intercepts derived from the single-factor capital asset pricing model (CAPM), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model. The rolling window analysis, which has not been used in prior sell-side analyst research, to the best of our knowledge, enables us to more effectively capture the time-varying portfolio performance over the long sample period, while the use of various single- and multi-factor models helps rule out the concern on the poor model of asset pricing raised by Barber et al. (2001).

Our empirical investigation proceeds in three main parts, showing some interesting results that are robust to alternative model specifications. In the first part, we examine the time-varying daily abnormal returns (both gross and net of transaction costs) to the *upgrade* and *downgrade* portfolios using the whole sample of analyst recommendation revisions. Specifically, on average, the *upgrade* portfolio generates no significantly positive abnormal gross (or net) returns in any period of time, suggesting that upgrades are in general valueless. In contrast, the *downgrade* portfolio generates significantly negative abnormal gross returns in several periods of time. For example, the negative abnormal gross returns to the *downgrade* portfolio are statistically significant, at least at the 5% level, from April 2001 to January 2003, ranging from −3.50 basis points to −6.40 basis points, and from March 2009 to June 2010, ranging from −3.45 basis points to −8.59 basis points. However, given the existence of massive portfolio rebalancing, the *downgrade* portfolio

³ Barber et al. (2001) point out that event-time analysis is a more analyst-oriented approach, which does not measure the profits to an implementable investment strategy (see, also, Stickel 1995; Womack 1996; Ivkovic and Jegadeesh 2004; Green 2006; Brown et al. 2009).

does not generate significant abnormal net returns after taking a reasonable level of transaction costs into account.

Although a large number of investment strategies based on analyst recommendation revisions fail to make profits after transaction costs, Barber et al. (2001, p. 537) argue that “it remains an open question whether other types of trading strategies could be profitable”. Inspired by Barber et al. (2001), we further employ two alternative investment strategies to assess: (1) whether analyst recommendation revisions made by high-ranking brokerage houses are more valuable in the UK; and (2) whether UK analyst recommendation revisions within specific industry sectors can make large enough profits to offset transaction costs.

On the one hand, it has been well reported that brokerage houses and their analysts, as repetitive players in the capital markets, obtain and accumulate their reputation capital, which is directly affected by the performance of stocks they recommend (see, Womack 1996; Brown et al. 2009). Therefore, it is possible that the superior performance made by some star sell-side analysts (e.g., those working for high-ranking brokerage houses) is balanced by the inferior performance made by their non-star counterparts (Fama and French 2010). In the second part of our empirical investigation, we replicate all analyses in the first part using a subsample of 11,016 analyst recommendation revisions exclusively made by the top 5 brokerage houses, measured by their positions on the annual All-Europe Research Team published by *Institutional Investor* (see “Appendix 1”). The subsample results, however, are qualitatively the same as those using the whole sample, suggesting that reputation of brokerage houses does not play a significant role in enhancing the investment value of sell-side analyst recommendation revisions in the UK.

On the other hand, prior sell-side analyst research controls for a wide range of stock characteristics (see, e.g., Stickel 1995; Womack 1996; Jegadeesh et al. 2004; Anderson et al. 2017), other than for industry factor. Jegadeesh et al. (2004, p. 1118) point out that “it is possible that analyst recommendation revisions reflect news about a firm’s competitive position in its industry”. Boni and Womack (2006) argue that upgrades and downgrades, aggregated across all sell-side analysts for stocks within each industry, might generate significant abnormal net returns, though they do not explicitly examine the transaction costs. Motivated by Jegadeesh et al. (2004) and Boni and Womack (2006), we conduct an industry-based analysis in the third part of our empirical investigation on the performance of the *upgrade* and *downgrade* portfolios within each industry sector, identified by the two-digit Industry Classification Benchmark (ICB) codes (see “Appendix 2”). Specifically, we find no significantly positive abnormal net returns to the *upgrade* portfolio within any industry sector in any period of time. However, within two high-tech industry sectors, i.e., Health Care (ICB 45) and Technology (ICB 95) sectors, the *downgrade* portfolio generates significantly negative abnormal net returns, at least at the 5% level, in several periods of time. For example, within Technology sector, the significantly negative abnormal net returns vary from -3.21 basis points to -6.44 basis points from September 2001 to March 2003, and vary from -2.44 basis points to -7.45 basis points from December 2006 to May 2010; similar evidence is found for the *downgrade* portfolio within Health Care sector. The reported incremental investment value is not only statistically significant, but also economically meaningful, suggesting the importance of controlling for the industry effect, which has never been explored in prior UK sell-side analyst research, to the best of our knowledge.

Thus far, our empirical investigation not only provides important evidence to complement the financial literature, but has significant implications for market participants. A natural question to ask is whether the reported portfolio performance in our empirical

investigation is simply as a result of random chance, i.e., sell-side analysts' luck. Another major contribution of this study is for the first time to introduce a rolling window-based *time-series* bootstrapping simulation method (see details in "Appendix 3"), to distinguish sell-side analysts' luck from their skill (Fama 1998; Barber et al. 2001). Specifically, our simulated results confirm that, on average (1) the observed insignificantly positive abnormal returns to the *upgrade* portfolio could be attributed to sell-side analysts' lack of skill in making valuable upward revisions (even before transaction costs), rather than their bad luck; and (2) sell-side analysts have certain skill in making valuable downward revisions (before transaction costs) over some periods of time, while such skill is not sufficient to cover the size of transaction costs, irrespective of whether these revisions are made by high-ranking brokerage houses or not. More importantly, our simulated results confirm that sell-side analysts do possess superior skill in making downward revisions for stocks with high-tech related characteristics over some periods of time, even after transaction costs.

Overall, this study contributes to sell-side analyst research in several important respects. First, this study employs a calendar-time approach to assess the performance of investment strategies based on UK sell-side analyst recommendation revisions, using a uniquely insightful database, *Morningstar Company Intelligence*, which has never been examined before. In addition, our industry-based analyses show that it is likely to make profits by short selling stocks with downward revisions within two high-tech industry sectors, i.e., Health Care and Technology sectors, over some periods of time even after transaction costs, the results of which could be mainly attributed to the greater coverage and efforts made by sell-side analysts on high-tech firms with substantial intangible assets (Barth et al. 2001; Barron et al. 2002). Finally, we develop a time-series bootstrapping simulation method to test whether the observed time-varying investment performance is due to random chance (i.e., sell-side analysts' luck), though our simulation method can be applied to distinguish luck from skill when evaluating the calendar-time portfolio performance in other types of investments.

The remainder of this paper is organized as follows. Sections 2 and 3 describe data and research design, respectively. Section 4 presents empirical and simulated results, while the final section concludes.

2 Data and sample description

We obtain the real-time sell-side analyst recommendations from the *Morningstar Extracted Data File: Historic Broker Recommendations for UK Registered and UK Listed Companies*, uniquely created by *Hemscott Company Guru*, now part of *Morningstar Company Intelligence*. Each stock recommendation record contains information on the name of the covered firm, the name of the brokerage house issuing the recommendation, the recommendation starting and expiration dates, and a rating between 1 and 9. A rating of 1 reflects a strong buy, 2 a buy, 3 a weak buy, 4 a weak buy/hold, 5 a hold, 6 a hold/sell, 7 a weak sell, 8 a sell, and 9 a strong sell. We exclude stock recommendations that omit the name of brokerage houses, those without releasing the expiration dates, and/or those with data errors. Also, we require that (1) the gap between the starting and expiration dates of each recommendation is less than 1 year to ensure that the brokerage house is actively following the recommended stock; and (2) the relevant financial and accounting data of the covered firms are available from the London Share Price Database (LSPD).

Our initial sample is comprised of 384,165 publicly available analyst recommendations made by 144 brokerage houses on 2905 distinct firms listed either on the main market of the LSE or on the AIM from January 1995 to June 2013. To allow for an easy and intuitive comparison with prior US studies, we reclassify all original analyst recommendations into five categories: Strong Buys (1 and 2; 44.99%), Buys (3 and 4; 10.66%), Holds (5; 32.43%), Sells (6 and 7; 3.68%), and Strong Sells (8 and 9; 8.24%). Brown et al. (2009) argue that prior sell-side analyst research is generally hampered by a very low proportion of negative recommendations (Sells and Strong Sells), e.g., 3.0% in the US (see, Barber et al. 2003). Table 1 shows that our *Morningstar* database overcomes this deficiency with much more negative recommendations, e.g., 11.92% of Sells and Strong Sells.

Sell-side analysts, however, often leave their stock recommendations unchanged for long periods of time; as a result, these stock recommendations become stale and less informative over time, potentially resulting in poor portfolio performance (see, Jegadeesh et al. 2004; Boni and Womack 2006; Jegadeesh and Kim 2006 and 2010; Hobbs et al. 2012). Therefore, our empirical investigation exclusively focuses on analyst recommendation revisions that convey more valuable information and have more predictive power over time. Table 2 presents the matrix of our final sample of 70,220 UK analyst recommendation revisions, i.e., 45.04% are Strong Buys and Buys, 38.73% are Holds, and 16.23% are Sells and Strong Sells, similar to those reported elsewhere (see, e.g., Stickel 1995; Barber et al. 2001; Boni and Womack 2006). The inclusion of 23,235 (33.09%) analyst recommendation revisions for 1042 dead firms in our sample also helps avoid the potential survivorship bias.

3 Research design

3.1 Portfolio construction

To evaluate the performance of calendar-time investment strategies, we construct two portfolios: (1) an *upgrade* portfolio, consisting of all stocks with upward revisions to Strong Buys or Buys from previous Strong Sells, Sells, or Holds; and (2) a *downgrade* portfolio, consisting of all stocks with downward revisions to Strong Sells, Sells, or Holds from previous Strong Buys or Buys. Specifically, to construct the *upgrade* portfolio, for each brokerage house, we identify upward revisions to Strong Buys or Buys from previous Holds, Sells, or Strong Sells during our sample period. The *upgrade* portfolio is updated daily; for each upward revision, the recommended stock enters the portfolio at the close of trading on the day the revision is announced. If an upward revision is announced on a non-trading day, the recommended stock is added into the *upgrade* portfolio at the close of the next trading day, and remains in the portfolio until the stock is either downgraded or dropped from coverage by the brokerage house.⁴ If a stock is recommended by more than one brokerage house on a given date, then that stock will appear multiple times in the *upgrade* portfolio on that date, once for each brokerage house. The *downgrade* portfolio is constructed in an analogous daily fashion.

⁴ A recent study of Rees et al. (2017) argues that sell-side analysts tend to strategically time the release of their recommendation revisions, in particular, to make downgrades on the weekends, as investor and media attention to analyst recommendation revisions is reduced on the weekends. However, this is not a serious concern about our sample, as only a total of 427 (0.76%) analyst recommendation revisions (187 upwards revisions and 240 downward revisions) are released on the weekends.

Table 1 Distribution of UK analyst recommendations

Year	No. of covered firms	No. of brokerage houses	Average duration	Average rating	No. of analyst recommendations	Analyst recommendation frequency									
						Strong Buy (1 and 2)		Buy (3 and 4)		Hold (5)		Sell (6 and 7)		Strong Sell (8 and 9)	
						No.	%	No.	%	No.	%	No.	%	No.	%
1995	861	28	92.7	4.23 [2.49]	12,516	4508	36.02	702	5.61	5526	44.15	263	2.10	1517	12.12
1996	1041	41	83.0	3.99 [2.35]	21,289	8234	38.68	1687	7.92	9000	42.28	502	2.36	1866	8.77
1997	1172	50	68.9	3.78 [2.21]	29,988	13,179	43.95	2520	8.40	11,409	38.05	676	2.25	2204	7.35
1998	1220	52	60.3	3.79 [2.23]	29,939	12,487	41.71	3826	12.48	10,214	34.12	1213	4.05	2199	7.34
1999	1167	50	67.9	3.64 [2.14]	26,274	11,308	43.04	4046	15.40	8373	31.87	997	3.79	1550	5.90
2000	1102	56	69.2	3.42 [2.01]	22,090	10,325	46.74	3647	16.51	6560	29.70	633	2.87	925	4.19
2001	1100	52	73.8	3.94 [2.33]	19,819	7639	38.54	2545	12.84	6855	34.59	1056	5.33	1724	8.70
2002	1061	49	83.7	3.92 [2.31]	17,928	7467	41.65	2041	11.38	5560	31.01	1146	6.39	1714	9.56
2003	1019	55	66.0	3.87 [2.26]	20,250	8768	43.30	2225	10.99	6264	30.93	1125	5.56	1868	9.22
2004	1038	60	62.0	3.85 [2.26]	23,621	10,096	42.74	2725	11.54	7546	31.95	1096	4.64	2158	9.14
2005	1111	59	61.2	4.02 [2.37]	24,976	9743	39.01	2737	10.96	8572	34.32	1302	5.21	2622	10.50
2006	1174	60	61.1	3.77 [2.20]	23,775	10,781	45.35	2514	10.57	7275	30.60	1237	5.20	1968	8.28
2007	1169	55	63.8	3.61 [2.10]	18,629	9151	49.12	1972	10.59	5398	28.98	742	3.98	1366	7.33
2008	1153	62	63.5	3.72 [2.16]	19,370	9776	50.47	1536	7.93	5329	27.51	696	3.59	2033	10.50
2009	1034	60	61.7	3.75 [2.18]	21,417	10,318	48.18	1987	9.28	6208	28.99	685	3.20	2219	10.36
2010	1003	44	70.3	3.34 [1.92]	16,794	9616	57.26	1366	8.13	4440	26.44	265	1.58	1107	6.59
2011	964	44	74.0	3.38 [1.95]	16,389	9175	55.98	1398	8.53	4440	27.09	254	1.55	1122	6.85
2012	947	44	69.2	3.43 [1.97]	13,587	7521	55.35	1066	7.85	3842	28.28	169	1.24	989	7.28
2013 (January to June)	724	33	69.8	3.66 [2.12]	5514	2741	49.71	413	7.49	1791	32.48	69	1.25	500	9.07
Overall	2905	144	68.0	3.75 [2.20]	384,165	172,833	44.99	40,953	10.66	124,602	32.43	14,126	3.68	31,651	8.24

This table presents the distribution of 384,165 UK analyst recommendations in each year from January 1995 to June 2013, in terms of the number of firms covered, the number of brokerage houses, and the average rating and number of analyst recommendations. All real-time analyst recommendations are obtained from *Morningstar Company Intelligence*. A rating of 1 reflects a strong buy, 2 a buy, 3 a weak buy, 4 a weak buy/hold, 5 a hold, 6 a hold/sell, 7 a weak sell, 8 a sell, and 9 a strong sell, which are reclassified into five categories: Strong Buy (1 and 2), Buy (3 and 4), Hold (5), Sell (6 and 7), and Strong Sell (8 and 9). We report the average rating for analyst recommendations in each year based on the nine-point rating scale, while in square brackets, we report the average rating based on the five-point rating scale. The average duration reflects the gap between the starting and expiration dates of analyst recommendations.

Table 2 Matrix of UK analyst recommendation revisions

From old rating	To new rating					Total	%
	Strong Buy (1 and 2)	Buy (3 and 4)	Hold (5)	Sell (6 and 7)	Strong Sell (8 and 9)		
Strong Buy (1 and 2)	–	5923	14,506	396	977	21,802	31.05
Buy (3 and 4)	5756	–	5242	682	204	11,884	16.92
Hold (5)	12,745	5267	–	2596	4927	25,535	36.36
Sell (6 and 7)	298	630	2410	–	844	4182	5.96
Strong Sell (8 and 9)	833	172	5043	769	–	6817	9.71
Overall	19,632	11,992	27,201	4443	6952	70,220	–
%	27.96	17.08	38.73	6.33	9.90	–	100.00

This table presents the matrix of 70,220 UK analyst recommendation revisions from January 1995 to June 2013. All real-time analyst recommendations are obtained from *Morningstar Company Intelligence*. A rating of 1 reflects a strong buy, 2 a buy, 3 a weak buy, 4 a weak buy/hold, 5 a hold, 6 a hold/sell, 7 a weak sell, 8 a sell, and 9 a strong sell, which are reclassified into five categories: Strong Buy (1 and 2), Buy (3 and 4), Hold (5), Sell (6 and 7), and Strong Sell (8 and 9)

Panel A of Table 3 presents the distribution of upward and downward revisions in the *upgrade* and *downgrade* portfolios, respectively, by the year of analyst recommendation revisions. The total number of sell-side analyst recommendation revisions included in the *upgrade* and *downgrade* portfolios, 56,075 (25,701 + 30,374), appears to be less than the total number of 70,220, as shown in Table 2, which is not surprising, however. The *upgrade* portfolio does not include stocks with upward revisions from Strong Sells to Holds, from Strong Sells to Sell, and from Sells to Holds, as they can also be interpreted as negative recommendations, while the *downgrade* portfolio does not include stocks with downward revisions from Strong Buy to Buy, as they can also be interpreted as positive recommendations (see, Stickel 1995; Brown et al. 2009). Panel B of Table 3 shows that no seasonal patterns are evident in the dataset.

3.2 Portfolio performance evaluation

We calculate the daily *value-weighted return from the upgrade and downgrade* portfolios on date t , $R_{p,t}$, as follows:

$$R_{p,t} = \sum_{i=1}^{n_{p,t-1}} \omega_{i,t-1} \times R_{i,t}, \quad (1)$$

where $R_{i,t}$ represents the daily return for the recommended stock i on date t ⁵; $n_{p,t-1}$ represents the number of revisions in the portfolio p as of the close of trading on date $t-1$; and

⁵ We explicitly exclude the return on the first trading day as many investors, particularly small investors, tend to react to information with a delay, as “it is impractical for them to engage in the daily portfolio rebalancing that is needed to respond to the changes” (Barber et al. 2001, p. 534). The value-weighted returns enable us to better capture the economic significance of our results, while the equal-weighted returns are, on average, biased upward due to the bid-ask bounce (see, Barber et al. 2001, 2003), that is, the returns of large size firms will be more heavily represented in the aggregate returns than those of small size firms (see, Lyon et al. 1999).

Table 3 Distribution of UK analyst recommendation revisions in the *upgrade* and *downgrade* portfolios by the year and month of analyst recommendation revisions

Year/Month	<i>Upgrade</i> portfolio				<i>Downgrade</i> portfolio			
	No. of covered firms	No. of broker-age houses	Average rating	No. of upward revisions	No. of covered firms	No. of broker-age houses	Average rating	No. of downward revisions
Panel A: year of analyst recommendation revisions								
1995	340	22	2.24 [1.15]	621	422	21	6.02 [3.68]	982
1996	603	37	2.25 [1.20]	1498	585	34	5.83 [3.54]	1715
1997	654	46	2.25 [1.23]	1978	654	45	5.87 [3.54]	2389
1998	660	37	2.28 [1.28]	1936	654	39	5.99 [3.59]	2395
1999	625	40	2.27 [1.28]	1993	618	41	5.86 [3.53]	1801
2000	513	39	2.25 [1.27]	1419	512	39	5.73 [3.45]	1496
2001	530	41	2.27 [1.26]	1331	616	40	6.03 [3.64]	2074
2002	567	41	2.28 [1.24]	1341	569	42	6.16 [3.74]	1480
2003	507	41	2.27 [1.22]	1165	566	39	6.02 [3.64]	1591
2004	578	43	2.26 [1.24]	1499	558	47	6.04 [3.65]	1818
2005	602	41	2.29 [1.28]	1628	629	45	6.01 [3.62]	2182
2006	575	44	2.27 [1.28]	1608	600	44	5.91 [3.56]	1834
2007	573	38	2.24 [1.24]	1581	544	41	5.83 [3.52]	1448
2008	488	41	2.21 [1.21]	1204	548	39	6.07 [3.67]	1680
2009	569	47	2.20 [1.19]	1849	560	48	5.97 [3.61]	1953
2010	470	39	2.21 [1.20]	1145	436	36	5.68 [3.43]	1192
2011	419	35	2.18 [1.18]	977	414	33	5.68 [3.43]	1022
2012	340	28	2.17 [1.16]	665	409	29	5.76 [3.49]	957
2013 (January-June)	192	24	2.22 [1.21]	263	234	22	5.83 [3.53]	365
Panel B: month of analyst recommendation revisions								
January	952	85	2.21 [1.21]	2501	1009	84	5.98 [3.61]	3352
February	848	86	2.24 [1.24]	2149	957	88	5.95 [3.59]	2603

Table 3 (continued)

Year/Month	Upgrade portfolio				Downgrade portfolio			
	No. of covered firms	No. of broker-age houses	Average rating	No. of upward revisions	No. of covered firms	No. of broker-age houses	Average rating	No. of downward revisions
March	913	79	2.26 [1.25]	2419	968	91	5.91 [3.57]	2691
April	876	84	2.23 [1.22]	2202	917	83	5.91 [3.57]	2342
May	849	77	2.27 [1.25]	2152	846	84	5.90 [3.57]	2254
June	845	76	2.27 [1.25]	2099	914	81	5.90 [3.57]	2265
July	870	86	2.25 [1.23]	2333	852	85	5.90 [3.57]	2700
August	758	80	2.25 [1.23]	1780	820	79	5.88 [3.55]	1949
September	857	78	2.23 [1.22]	2137	951	83	5.97 [3.60]	2680
October	930	81	2.28 [1.26]	2318	978	85	5.93 [3.59]	2935
November	848	81	2.26 [1.25]	2064	931	89	5.92 [3.58]	2630
December	773	79	2.22 [1.21]	1547	828	80	5.91 [3.57]	1973
Overall	1958	111	2.25 [1.24]	25,701	2081	109	5.93 [3.58]	30,374

This table presents on the distribution of 25,701 upward (30,374 downward) changes in analyst recommendations in the *upgrade* (*downgrade*) portfolio from January 1993 to June 2013 by the year (in Panel A) and month (in Panel B) of analyst recommendation revisions, in terms of the number of firms covered, the number of brokerage houses, as well as the average rating and number of analyst recommendation revisions. All real-time analyst recommendations are obtained from *Morningstar Company Intelligence*. A rating of 1 reflects a strong buy, 2 a buy, 3 a weak buy, 4 a weak buy/hold, 5 a hold, 6 a hold/sell, 7 a weak sell, 8 a sell, and 9 a strong sell, which are reclassified into five categories: Strong Buy (1 and 2), Buy (3 and 4), Hold (5), Sell (6 and 7), and Strong Sell (8 and 9). An *upgrade* portfolio consists of all stocks with upward revisions to Strong buys or Buys from previous Strong Sells, Sells, or Holds, while a *downgrade* portfolio consists of all stocks with downward revisions to Strong Sells, Sells, or Holds from previous Strong Buys or Buys. The *upgrade* portfolio does not include upward revisions from Strong Sells to Holds, from Strong Sells to Sells, and from Sells to Holds, which can also be interpreted as negative recommendations, while the *downgrade* portfolio does not include downward revisions from Strong Buys to Buys, which can also be interpreted as positive recommendations. We report the average rating for analyst recommendation revisions based on the nine-point rating scale, while in square brackets, we report the average rating based on the five-point rating scale

$\omega_{i,t-1}$ represents the weight of stock i in the portfolio p on date $t-1$, that is, the market value of stock i as of the close of trading on date $t-1$, divided by the aggregate market value of all stocks in the portfolio as of the close of trading on date $t-1$.

The abnormal return gross of transaction costs is estimated as the intercept term of α_p derived from the recent Fama and French (2015) five-factor model:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + r_p RMW_t + c_p CMA_t + \varepsilon_{p,t}, \quad (2)$$

where $R_{m,t}$ and $R_{f,t}$ represent the daily returns on the FTSE All-Share Index and on a 3-month UK T-bill, respectively; SMB_t , HML_t , RMW_t , and CMA_t represent the daily returns on zero-investment factor-mimicking portfolios for size, book-to-market (B/M), operating profitability, and investment, respectively⁶; and $\varepsilon_{p,t}$ represents the error term.

We estimate Eq. (2) repeatedly on a rolling window basis—a 1-year window length rolling one trading day forward—to track the performance of the underlying variables over time. Specifically, the first rolling window is from January 3, 1995 to December 29, 1995, covering 252 trading days, the typical number of trading days in a year in the UK stock market. Then a new observation (trading day) is added to the rolling window, while the first one is dropped, that is, we update the rolling window to include observations from January 4, 1995 to January 2, 1996, and so forth. In each rolling window, the five-factor regression yields parameter estimates of α_p , β_p , s_p , h_p , r_p , and c_p ; a significantly positive (negative) α_p indicates that the *upgrade* (*downgrade*) portfolio is profitable after controlling for risk factors of market, size, value, operating profitability, and investment. This calculation, therefore, generates a time series of 4420 daily abnormal gross returns to the *upgrade* or *downgrade* portfolio from January 1996 to June 2013.

To rule out the concern on the poor model of asset pricing—i.e., the newly introduced factors of operating profitability and investment in the Fama and French (2015) five-factor model might not be effective in the UK stock market and the momentum effect is also ignored (see, Barber et al. 2001; Brookfield et al. 2015)—we further estimate the CAPM, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p (R_{m,t} - R_{f,t}) + \varepsilon_{p,t}; \quad (3)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + \varepsilon_{p,t}; \quad (4)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + m_p MOM_t + \varepsilon_{p,t}, \quad (5)$$

where MOM_t represents the daily return on a zero-investment factor-mimicking portfolio for price momentum⁷; other variables are as defined in Eq. (2). In addition to parameter estimates of α_p and β_p generated in the single-factor regression, the three-factor regression yields parameter estimates of s_p and h_p , while the four-factor regression yields parameter estimates of s_p , h_p , and m_p .

⁶ Fama and French (2015, p. 1) argue that their five-factor model captures “the size, value, profitability, and investment patterns in average stock returns”. We construct the five factors in the UK stock market, strictly following Fama and French (Fama and French 1993, 2015).

⁷ We construct the momentum factor in the UK stock market, following Carhart (1997). For robustness purposes, we also estimate the CAPM, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model, using the daily returns on market, size, value, and momentum obtained from the Xfi Centre for Finance and Investment at University of Exeter (see, Gregory et al. 2013). Our results remain qualitatively the same, which are not reported for the sake of brevity, but are available on request.

3.3 Transaction costs

Timmermann and Granger (2004, p. 19) argue that return predictability “has to be seen in relation to the transaction costs of the asset. Predictable patterns only invalidate the EMH once they are large enough to cover the size of transaction costs.” Keim and Madhavan (1998) categorize transaction costs into explicit costs (e.g., brokerage commissions and taxes) and implicit costs (e.g., bid-ask spread and market impact of trading). Hudson et al. (1996) show that the total single-trip transaction costs in the UK for the most favored of investors is upward of 0.5%, including government stamp duty of 0.25%, negotiated brokerage commission of 0.05% (soft commissions could be zero if alternative services are offered in lieu of cash), and bid-ask spread of 0.25%. Based on a relatively cautious estimate of the average single-trip transaction costs in the UK for purchasing stocks at 0.75% and for short selling stocks at 1.5%,⁸ we further measure the corresponding average daily portfolio turnover multiplied by transaction costs in each rolling window.

Specifically, the daily turnover for the *upgrade* portfolio p on the trading date t is defined as the percentage of stocks in the portfolio as of the close of trading on date $t-1$ that has been sold off as of the close of trading on date t . That is, following Barber et al. (2001), we measure the daily turnover as the percentage of the portfolio that has been *turned over* into some other set of stocks on date t . First, for each stock i in the portfolio p as of the close of trading on date $t-1$, we calculate its fraction of the portfolio, $G_{i,t}$, at the end of trading on date t without accounting for portfolio rebalancing:

$$G_{i,t} = \omega_{i,t-1} \times (1 + R_{i,t}) / \sum_{i=1}^{n_{p,t-1}} \omega_{i,t-1} \times (1 + R_{i,t}) \quad (6)$$

where, as before, $R_{i,t}$ represents the daily return for the recommended stock i on date t ; $n_{p,t-1}$ represents the number of revisions in the portfolio p as of the close of trading on date $t-1$; and $\omega_{i,t-1}$ represents the weight of stock i in the portfolio p on date $t-1$, that is, the market value of stock i as of the close of trading on date $t-1$, divided by the aggregate market value of all stocks in the portfolio as of the close of trading on date $t-1$.

Second, $G_{i,t}$ is compared to the actual fraction, that is, stock i makes up of portfolio p as of the close of trading on date t , after accounting for any portfolio rebalancing. Finally, the change in the percentage holding of each stock on date $t-1$ is summed, generating the portfolio turnover on date t , $TURN_{p,t}$ ⁹:

$$TURN_{p,t} = \sum_{i=1}^{n_{p,t}} |G_{i,t} - F_{i,t}|, \quad (7)$$

⁸ Barber et al. (2001) report that the abnormal net returns are not significantly greater than zero after accounting for the average single-trip transaction costs of 0.65% in the US. Despite the lack of readily available data regarding short selling costs in the UK, we assume a short selling cost of 0.75%, according to Ellis and Thomas (2004) and Li et al. (2009).

⁹ We calculate the portfolio turnover accounting for both increase and decrease in stock weight. For example, we adjust the *upgrade* portfolio by buying new stocks with upward revisions and simultaneously selling existing stocks when their upward revisions are dropped or downgraded on a daily basis; the increase in stock weight equals to the decrease in stock weight at the portfolio level (see, Barber et al. 2001). Therefore, the total portfolio turnover = $2 \times$ the decrease (or increase) in stock weight: $\sum_{i=1}^{n_{p,t}} |G_{i,t} - F_{i,t}| = \sum_{i=1}^{n_{p,t}} \max\{(G_{i,t} - F_{i,t}), 0\} \times 2$.

where $n_{p,t}$ represents the number of revisions in the portfolio p as of the close of trading on date t ; $G_{i,t}$ represents the calculated weight of stock i in the portfolio p as of the close of trading on date $t-1$ without accounting for portfolio rebalancing; and $F_{i,t}$ represents the actual weight that stock i in the portfolio p at the end of trading on date t after any portfolio rebalancing.

Finally, in each rolling window, we calculate the abnormal net return as the abnormal gross return less the estimated single-trip transaction costs multiplied by the corresponding daily portfolio turnover¹⁰:

$$\text{Abnormal net return} = \text{Abnormal gross return} (\alpha_p) - \text{single-trip transaction costs} \times \text{TURN}_{p,t}. \quad (8)$$

4 Empirical and simulated results

In this section, we focus on presenting the empirical and simulated results under the Fama and French (2015) five-factor model, though our results remain qualitatively unchanged under the CAPM, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model. These results are not presented for the sake of brevity, but are available on request.

4.1 Time-varying portfolio performance

4.1.1 Abnormal gross returns

Figure 1a illustrates the time-varying daily abnormal returns gross of transaction costs to the *upgrade* portfolio, along with the corresponding t -statistics. Overall, the *upgrade* portfolio does not generate any significantly positive abnormal gross returns in any period of time, but generate significantly negative abnormal gross returns in several periods of time. Specifically, the abnormal gross returns initially fluctuate around zero, and then become significantly negative, at least at the 5% level, from August 2001 to July 2003, ranging from -3.80 basis points to -6.49 basis points. After that, the significantly negative abnormal gross returns are also observed in two short periods of time: (1) from August 2006 to January 2007, ranging from -2.42 basis points to -4.27 basis points; and (2) from August 2008 to November 2008, ranging from -4.55 basis points to -6.02 basis points. Our empirical results suggest that upgrades are generally valueless in the UK, as they could not generate significantly positive abnormal returns (even before transaction costs). Therefore, from an investor's perspective, it is unlikely to make profits by purchasing stocks with upward revisions in any period of time and, even worse, it is likely to suffer significant losses over some periods of time.

Figure 1b illustrates the time-varying daily abnormal returns gross of transaction costs to the *downgrade* portfolio, along with the corresponding t -statistics. Importantly, the *downgrade* portfolio generates significantly negative abnormal gross returns in several periods of time, at least at the 5% level. For example, we find significantly negative abnormal gross returns, which range from -3.50 basis points to -6.40 basis points from

¹⁰ The unreported daily turnover for the *upgrade* portfolio ranges from 1.41 to 1.83%, with an average of 1.61% over the whole sample period; the average daily turnover for the *downgrade* portfolio ranges from 1.37 to 1.89%, with an average of 1.63%, which is close to that reported in the US (see, Barber et al. 2001).

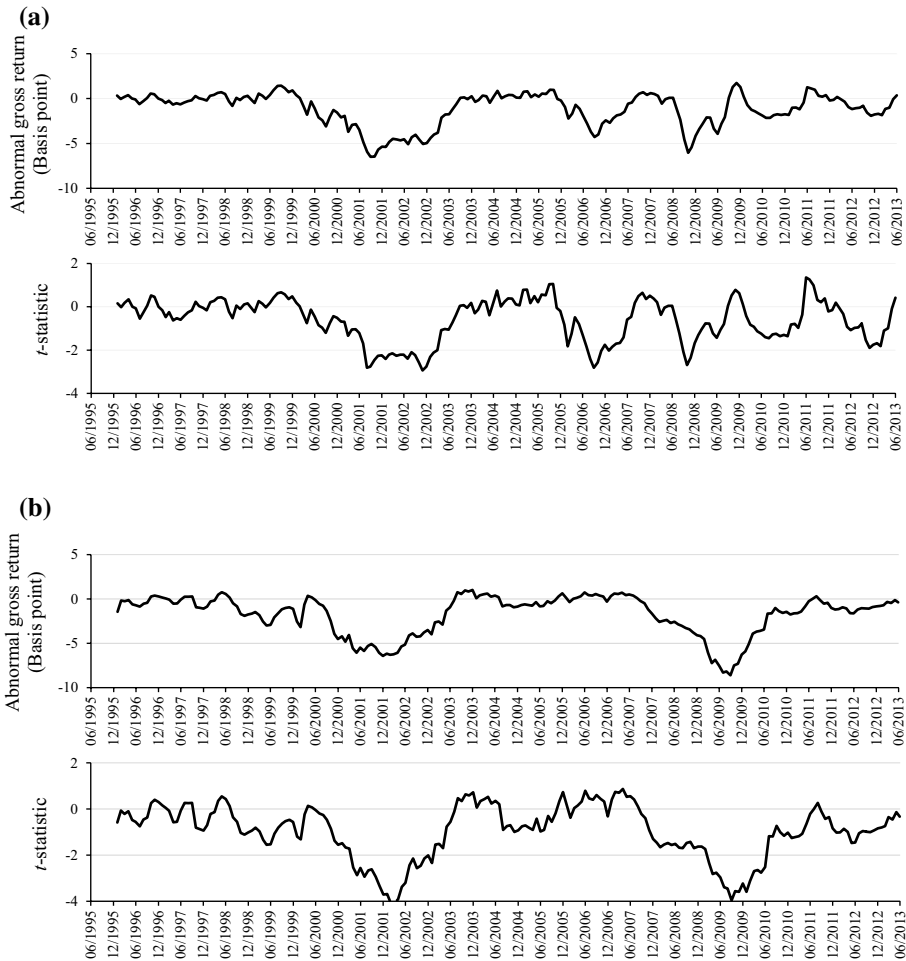


Fig. 1 The time-varying daily abnormal gross returns to the **a** *upgrade* and **b** *downgrade* portfolios and the corresponding *t*-statistics under the Fama and French (2015) five-factor model, using the whole sample of UK analyst recommendation revisions

April 2001 to January 2003, and range from -3.45 basis points to -8.59 basis points from March 2009 to June 2010. This suggests that, on average, downgrades have certain investment value and that it is likely for investors to make profits by short selling stocks with downward revisions over some periods of time (before transaction costs).

4.1.2 Abnormal net returns

Figures 2a, b illustrates the time-varying average daily abnormal returns net of transaction costs to the *upgrade* (*downgrade*) portfolio, along with the corresponding *t*-statistics. We find no significantly positive (negative) abnormal net returns to the *upgrade* (*downgrade*) portfolios in any period of time, suggesting that it is unlikely for investors to make profits by purchasing (short selling) stocks with upward (downward) revisions after taking a

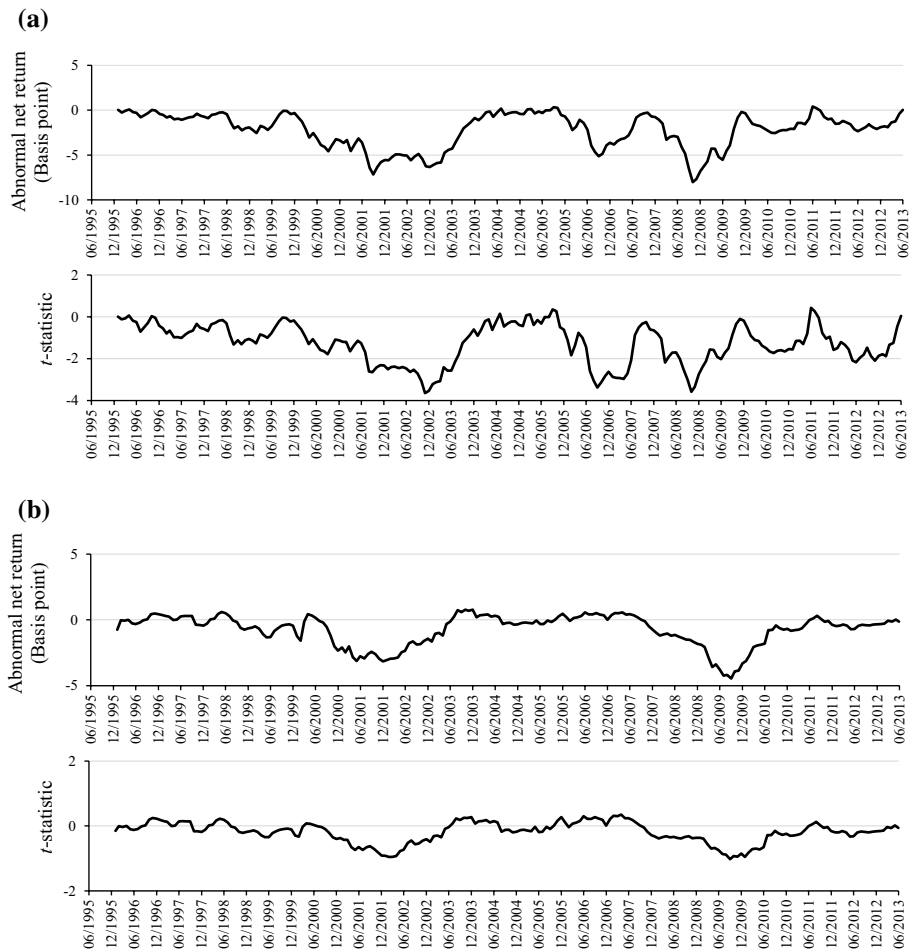


Fig. 2 The time-varying daily abnormal net returns to the **a** *upgrade* and **b** *downgrade* portfolios and the corresponding *t*-statistics under the Fama and French (2015) five-factor model, using the whole sample of UK analyst recommendation revisions

reasonable level of transaction costs into account, in line with Barber et al. (2001). Therefore, the observed market inefficiencies disappear after transaction costs, that is, the significantly negative abnormal gross returns to the *downgrade* portfolios in several periods of time, as illustrated in Fig. 1b, are actually not exploitable by investors.¹¹

¹¹ We thank an anonymous reviewer for suggesting that the transaction costs should be taken into account for both the portfolio and benchmarks when calculating the abnormal net return of the *upgrade* and *downgrade* portfolios. Based on the gross Fama and French (2015) five factors in the UK, we further construct the tradable factors. Specifically, the net return of each tradable factor portfolio is measured as the gross return of the corresponding factor portfolio less the portfolio turnover multiplied by transaction costs. Following Novy-Marx and Velikov (2016), we rebalance the underlying portfolios for the Fama and French (2015) factors annually, at the end of every June. We then reestimate the abnormal net return to the *upgrade* or *downgrade* portfolio by regressing the net portfolio return (the gross portfolio return net of transaction costs) against the tradable Fama and French (2015) five factors. Our overall conclusions hold up fairly well; our results based on the tradable Fama and French (2015) five factors are not presented to save space, but are available on request.

4.2 Alternative investment strategies

4.2.1 High-ranking brokerage houses

A growing body of sell-side analyst research shows the existence of skill differences among sell-side analysts, and those sell-side analysts with higher reputation (or star sell-side analysts) are more able to make more valuable stock recommendations (see, Stickel 1995; Hong and Kubik 2003; Fang and Yasuda 2014; Kucheev et al. 2017). Ljungqvist et al. (2009) argue that the ranking of sell-side analysts in the *Institutional Investor* annual poll is the most important driver of their career outcomes. If investors realize that an analyst provides them with wrong information on purpose, the damage to the analyst's reputation would be immediate and long-lasting. Sell-side analysts, as repetitive players in the capital markets, obtain and accumulate their reputation capital, and invariably attempt to protect their reputation capital by reducing the probability of becoming involved with misleading stock recommendations. As more prestigious brokerage houses are able to attract and employ star sell-side analysts, we expect analyst recommendation revisions made by high-ranking brokerage houses to be more valuable.¹²

Specifically, we construct two alternative *upgrade* and *downgrade* portfolios, using a subsample of 11,016 analyst recommendation revisions made exclusively by the top 5 brokerage houses, identified by their 3-year moving average ($t-3$, $t-2$, $t-1$) of positions on the annual All-Europe Research Team published by *Institutional Investor* (see details in "Appendix 1"). Repeating all empirical analyses in Sect. 4.1, we find quite similar results to those using the whole sample. For example, Figs. 3a and 4a show that the *upgrade* portfolio fails to generate any significantly positive abnormal gross (net) returns in any period of time before (after) transaction costs. Figure 3b shows that the *downgrade* portfolio generates significantly negative abnormal gross returns, at least at the 5% level, which range from -3.74 basis points to -8.57 basis points from January 2001 to March 2003, and range from -3.79 basis points to -8.68 basis points from December 2008 to March 2010. However, these observed significantly negative abnormal returns to the *downgrade* portfolio disappear after transaction costs (see Fig. 4b).

Overall, we conclude that the reputation of brokerage houses does not play an important role in making valuable upward and downward revisions in the UK. That is, it is unlikely for investors to make profits (after transaction costs) by following analyst recommendation revisions in the UK, irrespective of whether they are made by high-ranking brokerage houses or not. This seems different from that reported in the US, but the discrepancy could be explained by the less influence of the annual All-European Research Team published by *Institutional Investor* on UK sell-side analysts' career concern, compared with the influence of its US counterpart.

¹² The *Morningstar* database does provide information on individual sell-side analysts issuing stock recommendations, so we focus on the reputation of brokerage houses, which is supposed to be positively correlated with the reputation of individual sell-side analysts (see Brown et al. 2009).

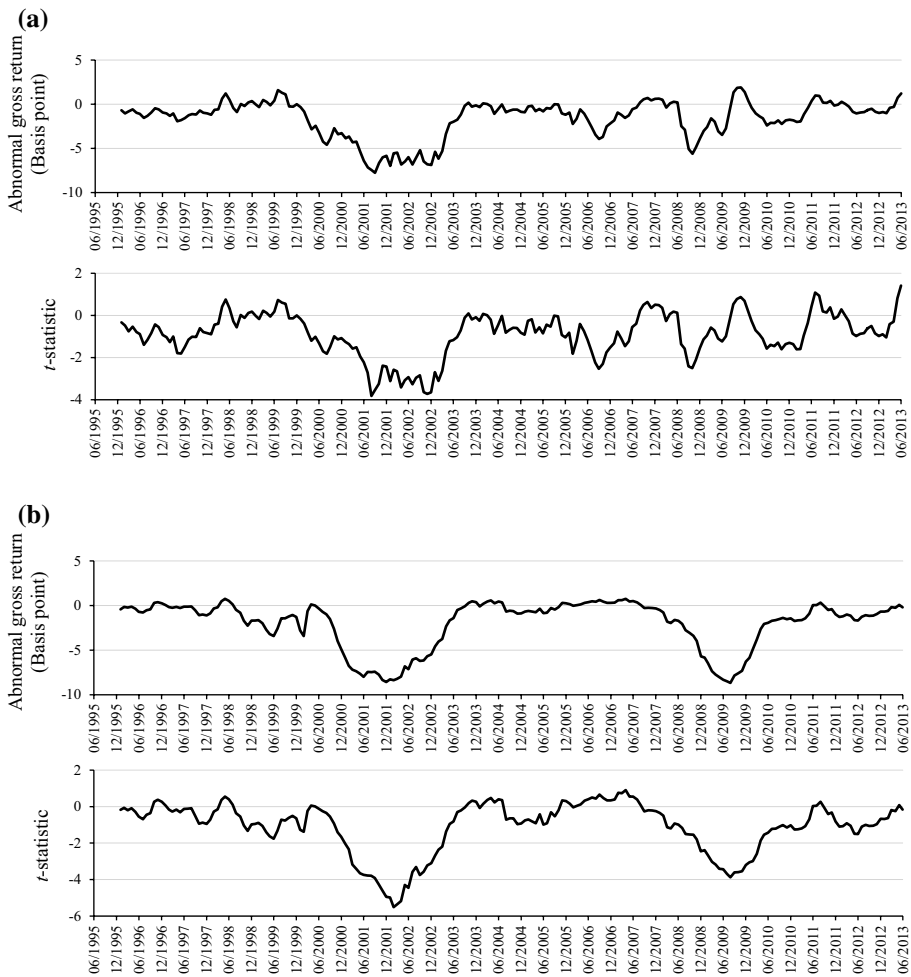


Fig. 3 The time-varying daily abnormal gross returns to the **a** *upgrade* and **b** *downgrade* portfolios and the corresponding *t*-statistics under the Fama and French (2015) five-factor model, using the subsample of UK analyst recommendation revisions made by the top 5 brokerage houses

4.2.2 Industry-based investment strategies

Prior sell-side analyst research emphasizes the importance of controlling for various firm-specific characteristics of the recommended stocks, e.g., size, value, trading volume, price momentum, earnings, and so on (see, Stickel 1995; Womack 1996; Jegadeesh et al. 2004; Anderson et al. 2017). Little attention has been paid to industry, though it has been well demonstrated to have predictive value for stock returns (see, Markowitz and Grinblatt 1999; Boni and Womack 2006). In this subsection, we conduct an industry-based analysis to assess whether analyst recommendation revisions for stocks within specific industry sectors in the UK can make large enough profits to cover the size of transaction costs.

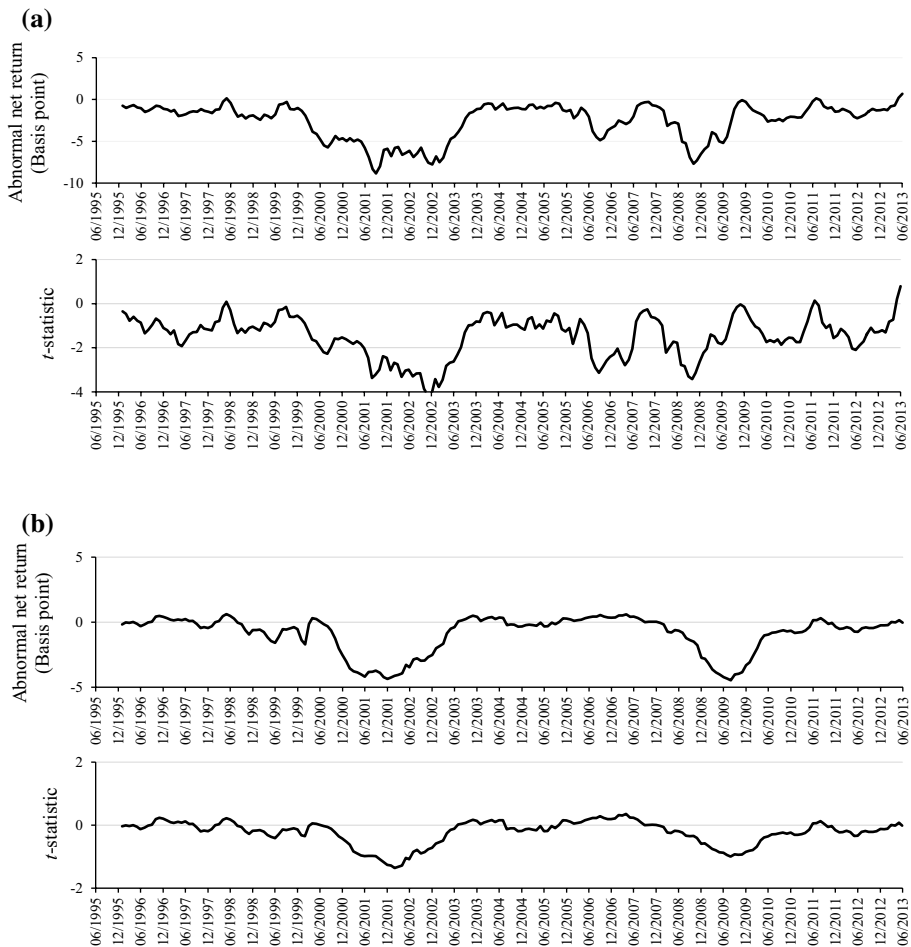


Fig. 4 The time-varying daily abnormal net returns to the **a** *upgrade* and **b** *downgrade* portfolios and the corresponding *t*-statistics under the Fama and French (2015) five-factor model, using the subsample of UK analyst recommendation revisions made by the top 5 brokerage houses

Overall, we find no significantly positive abnormal net returns to the *upgrade* portfolio within any industry sector in any period of time, again suggesting that upgrades have no investment value in the UK, consistent with our early results (see Figs. 2a, 4a). However, we find some important evidence showing significantly negative abnormal net returns to the *downgrade* portfolio over some periods of time within two high-tech industry sectors, i.e., Health Care (ICB 45) and Technology (ICB 95) sectors. In this subsection, we focus on presenting the time-varying daily abnormal net returns to the *downgrade* portfolios within Health Care and Technology sectors. The insignificantly positive (negative) abnormal returns to the *upgrade* (*downgrade*) portfolio within other industry sectors are not reported to save space, but are available on request.

Figure 5a, b illustrates the time-varying daily abnormal net returns to the *downgrade* portfolio, along with the corresponding *t*-statistics, within Health Care and Technology sectors, respectively. Specifically, Fig. 5a shows that, within Health Care sector, the

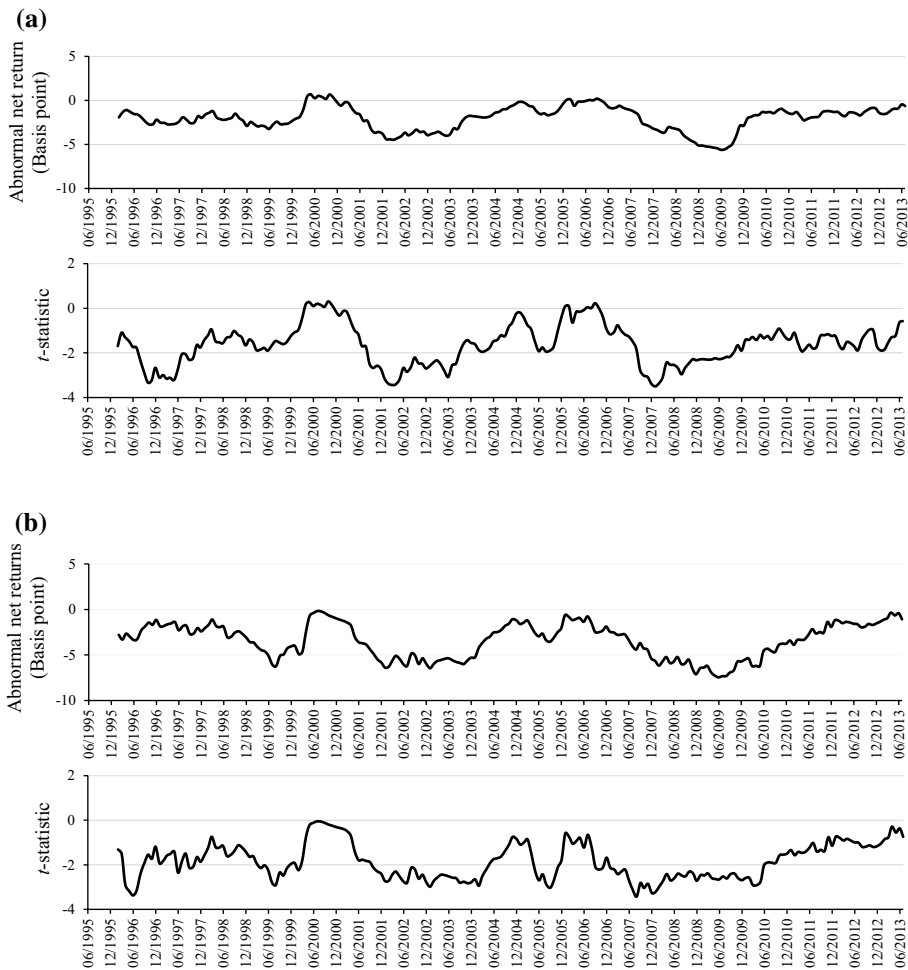


Fig. 5 The time-varying daily abnormal net returns to the *downgrade* portfolio and the corresponding *t*-statistics under the Fama and French (2015) five-factor model, within **a** Health Care (ICB 45) sector and **b** Technology (ICB 95) sector

downgrade portfolio generates significantly negative abnormal net returns, at least at the 5% level, in several periods of time. For example, the significantly negative abnormal net returns range from -1.94 basis points to -2.73 basis points from July 1996 to September 1997, range from -2.51 basis points to -4.47 basis points from August 2001 to August 2003, and range from -2.58 basis points to -5.61 basis points from August 2007 to August 2009. Similarly, within Technology sector, the significantly negative abnormal net returns to the *downgrade* portfolio are observed in several periods of time, at least at the 5% level (see Fig. 5b). For example, the significantly negative abnormal net returns range from -3.21 basis points to -6.44 basis points from September 2001 to March 2003, and range from -2.44 basis points to -7.45 basis points from December 2006 to May 2010.

These negative abnormal net returns to the *downgrade* portfolio within the two industry sectors are not only statistically significant, but also economically meaningful, suggesting

the importance of controlling for the industry effect. From an investor's perspective, it is likely to make profits by short selling stocks with downward revisions with high-tech related characteristics over some periods of time, even after transaction costs, though upward revisions are valueless in any industry sector. Our results confirm that short signals are more valuable than long signals (see, e.g., Barber et al. 2001; Jegadeesh et al. 2004; Ryan and Taffler 2006).¹³

Furthermore, our results could be mainly attributed to the greater coverage and efforts made by sell-side analysts on high-tech firms (Barth et al. 2001; Barron et al. 2002; Hirshleifer et al. 2018). More specifically, high-tech firms have more unrecognized intangible assets, which reflect greater economic benefits from knowledge-based activities in the future. These high-tech firms, therefore, attract more attention from investment community and enjoy greater coverage; analyst coverage, in turn, improves the efficiency of communicating private information to investors (see, Barron et al. 2002; Sun 2011).

Given that intangible assets are typically unrecognized in the financial statements, high-tech firms are associated with more complex information, which provides opportunities for sell-side analysts to benefit from the application of their expertise (Barth et al. 2001; Barron et al. 2002; Hirshleifer et al. 2018). Sell-side analysts, therefore, expend more intense efforts to cover high-tech firms. In particular, the rapid development of the Internet has greatly enhanced the accessibility of various information, helping sell-side analysts make more valuable recommendations for stocks with high-tech related characteristics (Kwon 2002). Also, Gu and Wang (2005) argue that information complexity may vary by the regulatory environment. Specifically, less complex information is related to firms within Health Care sector, e.g., biotech and pharmaceutical firms and firms manufacturing equipment used in medical treatment, due to the highly stringent and comprehensive regulations in the approval process of new drugs and new medical equipment. The transparency in the innovation process thus improves sell-side analysts' abilities in making valuable stock recommendations within Health Care sector.

4.3 Bootstrapping simulations

Our empirical results in Sects. 4.1 and 4.2 not only provide important evidence to supplement the financial literature, but also have significant implications for market participants. A natural question to ask is whether the reported abnormal returns are as a result of sell-side analysts' skill or their luck (Fama 1998; Barber et al. 2001). To address this concern, we develop a *time-series* bootstrapping simulation method to distinguish sell-side analysts' luck from their skill. In this subsection, our simulated results mirror the three main parts of our empirical results. We focus on presenting the distribution of the *t*-statistics of the abnormal returns rather than the actual abnormal returns, as the *t*-statistic scales the abnormal return by its standard errors and thus has superior statistical properties (see, Fama and French 2010). Specifically, we compare the values of the *t*-statistics at selected percentiles of cumulative distribution function (CDF) of the actual *t*-statistics with the averages

¹³ In general, investors are more likely to purchase stocks following positive recommendations, as it is more expensive to short sell (see, Irvine 2004; Jackson 2005; Mehran and Stulz 2007). As a result, in order to benefit from more trading, brokerage houses could make positively biased recommendations for stocks that actually do not have real investment value. By acting this way in the long term, brokerage houses and their analysts will lose their credibility as investors tend to discount the value of positive recommendations, causing long signals to be less valuable.

Table 4 Percentiles of *t*-statistics for actual and simulated abnormal returns under the Fama and French (2015) five-factor model, using the whole sample of UK sell-side analyst recommendation revisions

%	Upgrade portfolio			Downgrade portfolio		
	Simulated <i>t</i> -stat	Actual <i>t</i> -stat	% (simulated < actual)	Simulated <i>t</i> -stat	Actual <i>t</i> -stat	% (simulated < actual)
Panel A: abnormal gross returns						
1	-2.47	-3.27	1.93	-2.76	-3.11	0.16
2	-2.06	-2.85	2.24	-2.35	-2.77	0.31
3	-1.87	-2.62	2.93	-2.08	-2.51	0.71
4	-1.75	-2.46	2.94	-1.93	-2.35	0.70
5	-1.64	-2.34	3.02	-1.78	-2.21	1.39
10	-1.27	-1.88	3.24	-1.35	-1.81	1.69
20	-0.83	-1.37	6.85	-0.87	-1.27	2.22
30	-0.52	-1.01	9.88	-0.50	-0.85	3.61
40	-0.25	-0.67	14.45	-0.21	-0.51	5.46
50	-0.01	-0.41	18.62	0.05	-0.20	8.98
60	0.24	-0.15	23.35	0.26	0.11	12.17
70	0.50	0.14	30.80	0.45	0.37	15.17
80	0.81	0.53	36.74	0.65	0.64	28.70
90	1.25	1.01	37.04	0.87	0.95	57.47
95	1.61	1.42	39.58	1.07	1.23	69.75
96	1.72	1.53	40.82	1.13	1.35	77.19
97	1.84	1.67	41.28	1.23	1.48	85.27
98	2.02	1.82	42.42	1.38	1.78	92.63
99	2.32	1.95	43.56	1.79	1.92	95.30
Panel B: abnormal net returns						
1	-2.97	-3.71	0.03	-0.94	-1.22	0.06
2	-2.56	-3.32	0.04	-0.75	-1.04	0.11
3	-2.37	-2.98	0.05	-0.65	-0.95	0.27
4	-2.25	-2.81	0.06	-0.58	-0.90	0.27
5	-2.14	-2.67	0.06	-0.52	-0.85	0.52
10	-1.77	-2.18	0.07	-0.32	-0.67	0.64
20	-1.33	-1.73	0.08	-0.08	-0.41	0.83
30	-1.02	-1.46	0.12	0.10	-0.19	1.37
40	-0.75	-1.25	0.30	0.26	-0.01	2.07
50	-0.53	-1.04	0.69	0.40	0.14	3.40
60	-0.33	-0.85	2.80	0.52	0.28	4.60
70	-0.13	-0.62	3.26	0.65	0.43	5.73
80	0.11	-0.37	5.60	0.78	0.58	10.85
90	0.55	-0.03	9.56	0.97	0.75	21.72
95	0.98	0.03	12.54	1.15	0.87	26.36
96	1.12	0.12	24.73	1.21	0.91	29.17
97	1.30	0.22	27.06	1.28	0.96	36.09
98	1.52	0.38	31.23	1.45	1.05	37.63
99	1.82	0.64	35.35	1.79	1.13	38.96

Table 4 (continued)

This table presents the values of t -statistics at selected percentiles (%) of the distribution of t -statistics of the actual and simulated abnormal returns, as well as the percentage of the 5000 simulation runs that produce lower values of t -statistics at the selected percentiles than those actual abnormal returns (% simulated < actual) for the *upgrade* and *downgrade* portfolios, using the whole sample of UK analyst recommendation revisions from January 1996 to June 2013. The abnormal gross return is estimated as the intercept term derived from the Fama and French (2015) five-factor model. The abnormal net return is calculated as the abnormal gross return less the estimated single-trip transaction costs for purchasing stocks at 0.75% and for short selling those at 1.5%, multiplied by the corresponding average daily portfolio turnover

of the 5000 simulated t -statistics at the same percentiles. If the actual t -statistics is higher than 95% of the 5000 simulated t -statistics, we reject the null hypothesis that the abnormal return is due to random chance (sell-side analysts' luck) at the 95% confidence level and vice versa.

4.3.1 Simulated results based on the whole sample

Table 4 shows the CDFs of the actual t -statistics of the abnormal returns (both gross and net of transaction costs) and the average of the simulated CDFs for the *upgrade* and *downgrade* portfolios, based on the whole sample. The left side of Panel A shows that for the *upgrade* portfolio, the actual t -statistics of the abnormal gross returns are always smaller than the corresponding average values from the simulations for all percentiles. For example, the left tail 5th and 10th percentiles of the actual t -statistics are -2.34 and -1.88 , respectively, smaller than the corresponding average values of -1.64 and -1.27 from the simulations. Similarly, the right tail 90th and 95th percentiles of the actual t -statistics are 1.01 and 1.42, respectively, smaller than the average values of 1.25 and 1.61 from the simulations. The simulated results clearly suggest sell-side analysts' lack of skill in making valuable upward revisions for stocks that can generate significantly positive abnormal returns (even before transaction costs). It is not surprising that, in the left side of Panel B, for the *upgrade* portfolio, the actual t -statistics of the abnormal net returns are far below the average values from the simulations for all percentiles, again confirming that sell-side analysts do not possess sufficient skill in making valuable upward revisions in any period of time. Figure 6a, b illustrates the CDFs of the actual t -statistics of the abnormal gross (net) returns and the corresponding average simulated CDFs for the *upgrade* portfolio.

The right side of Panel A shows that for the *downgrade* portfolio, the left tail percentiles of the actual t -statistics of the abnormal gross returns are far below the corresponding average values from the simulations. For example, the 5th and 10th percentiles of the actual t -statistics are -2.21 and -1.81 , respectively, much lower than the average values of -1.78 and -1.35 from the simulations. In contrast, the right tail percentiles of the actual t -statistics suggest that sell-side analysts have certain skill in making valuable downward revisions over some periods of time (at least before transaction costs). For example, the 90th and 95th percentiles of the actual t -statistics are 0.95 and 1.23, respectively, higher than the average values of 0.87 and 1.07 from the simulations. However, the observed superior skill does not show up more generally in the abnormal net returns as they are absorbed by transaction costs. Specifically, the right side of Panel B shows that for the *downgrade* portfolio, the actual t -statistics of the abnormal net returns are always smaller than the corresponding average values from the simulations for all percentiles, suggesting sell-side analysts' lack of enough skill in making valuable downward revisions for stocks that can generate significant abnormal returns to cover the size of transaction costs in any period of

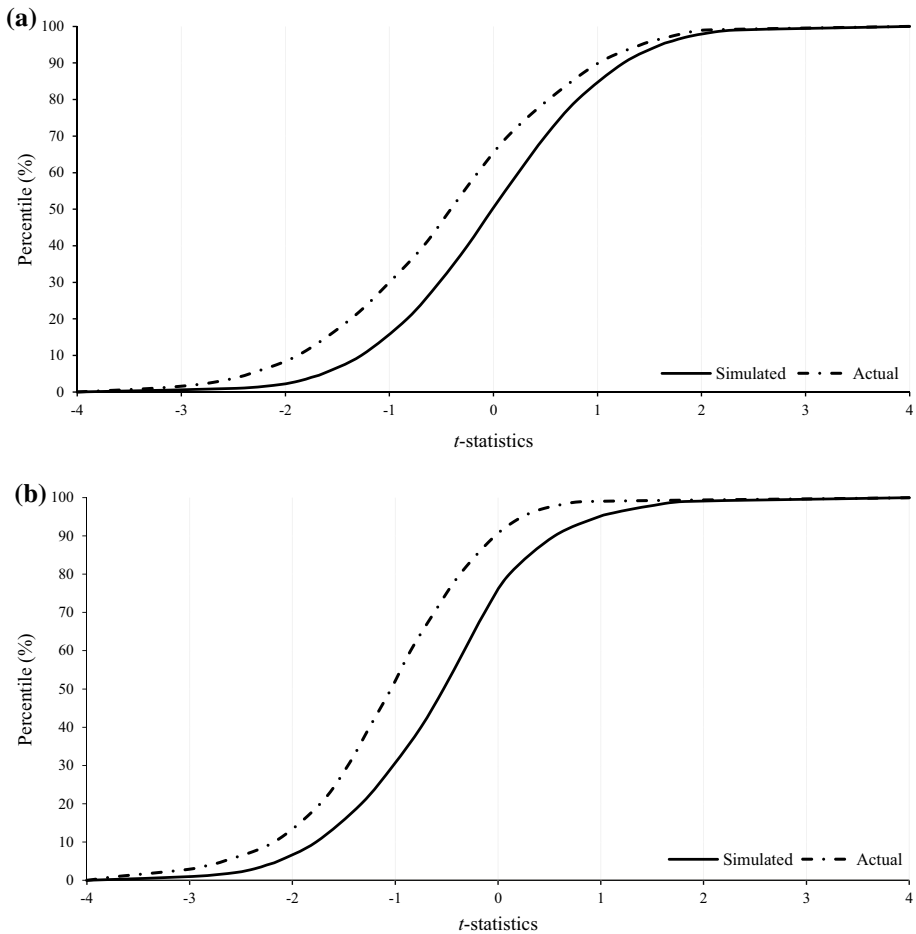


Fig. 6 Simulated and actual cumulative density function (CDF) of t -statistics for the abnormal **a** gross returns and **b** net returns to the *upgrade* portfolio, under the Fama and French (2015) five-factor model, using the whole sample

time. Figure 7a, b illustrates the CDFs of the actual t -statistics of the abnormal gross (net) returns and the corresponding average simulated CDFs for the *downgrade* portfolio.

4.3.2 Simulated results based on the subsample made by the top 5 brokerage houses

We turn now to simulations that use the subsample of analyst recommendation revisions made by the top 5 brokerage houses. Table 5 shows that our subsample simulated results are qualitatively similar to those based on the whole sample, as shown in Table 4, confirming that the reputation of brokerage houses does not matter. That is, on average, even sell-side analysts working for high-ranking brokerage houses have not enough skill to make valuable upward or downward revisions for stocks that can produce abnormal returns to offset the size of transaction costs in any period of time.

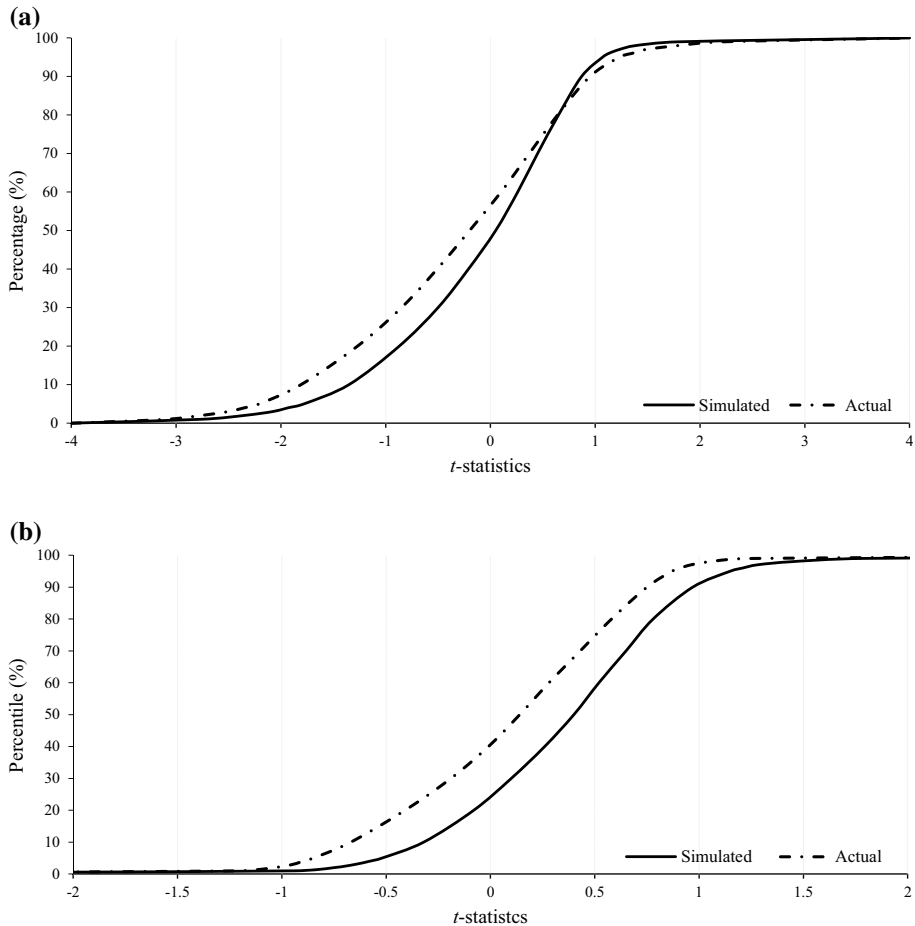


Fig. 7 Simulated and actual cumulative density function (CDF) of t -statistics for the abnormal **a** gross returns and **b** net returns to the *downgrade* portfolio, under the Fama and French (2015) five-factor model, using the whole sample

4.3.3 Simulated results within two high-tech industry sectors

Finally, our early results in Fig. 5a, b imply that it is likely for investors to make profits after transaction costs, by short selling stocks with downward revisions, within two high-tech industry sectors, i.e., Health Care (ICB 45) and Technology (ICB 95) sectors, respectively. Table 6 reports the CDFs of the actual t -statistics of the abnormal net returns and the average of the simulated CDFs for the *upgrade* and *downgrade* portfolios, within the two high-tech industry sectors.¹⁴ Specifically, the left side of Panels A and B of Table 6 shows

¹⁴ We also conduct bootstrapping simulations within other industry sectors, showing that sell-side analysts do not possess sufficient skill in making valuable upward or downward revisions over the whole sample period, the results of which are not reported for the sake of brevity, but are available on request.

Table 5 Percentiles of *t*-statistics for actual and simulated abnormal returns under the Fama and French (2015) five-factor model, using the subsample of UK sell-side analyst recommendation revisions made by the top 5 brokerage houses

%	Upgrade portfolio			Downgrade portfolio		
	Simulated <i>t</i> -stat	Actual <i>t</i> -stat	% (simulated < actual)	Simulated <i>t</i> -stat	Actual <i>t</i> -stat	% (simulated < actual)
Panel A: abnormal gross returns						
1	-2.63	-3.26	1.74	-2.67	-3.04	0.15
2	-2.10	-2.83	2.27	-2.22	-2.62	0.29
3	-1.88	-2.61	2.37	-1.98	-2.44	0.68
4	-1.72	-2.46	2.64	-1.83	-2.30	0.67
5	-1.62	-2.34	2.65	-1.73	-2.00	1.33
10	-1.26	-1.93	3.10	-1.38	-1.36	1.62
20	-0.85	-1.42	6.21	-0.88	-1.09	2.12
30	-0.54	-1.06	9.34	-0.53	-0.66	3.47
40	-0.26	-0.74	10.93	-0.21	-0.25	5.25
50	-0.01	-0.48	13.42	0.05	0.12	8.65
60	0.24	-0.20	17.05	0.30	0.45	11.74
70	0.52	0.11	22.49	0.47	0.65	14.66
80	0.85	0.46	26.53	0.69	1.03	27.78
90	1.27	0.98	31.69	0.99	1.47	55.72
95	1.59	1.40	34.39	1.25	1.62	67.74
96	1.70	1.52	35.29	1.34	1.75	75.09
97	1.84	1.66	36.30	1.48	1.78	83.10
98	2.11	1.88	37.54	1.67	1.88	92.33
99	2.64	1.92	38.27	1.88	1.94	95.32
Panel B: abnormal net returns						
1	-2.70	-3.74	0.02	-1.21	-1.40	0.06
2	-2.16	-3.35	0.04	-0.85	-1.31	0.11
3	-1.94	-3.12	0.04	-0.71	-1.08	0.27
4	-1.77	-2.98	0.05	-0.66	-0.94	0.26
5	-1.66	-2.85	0.05	-0.55	-0.84	0.51
10	-1.29	-1.89	0.06	-0.39	-0.80	0.62
20	-0.87	-1.50	0.08	-0.08	-0.76	0.82
30	-0.55	-1.40	0.09	0.03	-0.52	1.34
40	-0.27	-1.05	0.19	0.22	-0.30	2.04
50	-0.01	-0.80	0.50	0.46	-0.07	3.35
60	0.25	-0.67	2.14	0.54	0.11	4.55
70	0.53	-0.47	2.78	0.79	0.26	5.68
80	0.87	-0.24	4.51	0.91	0.48	10.78
90	1.30	-0.02	8.18	1.03	0.57	21.65
95	1.63	0.03	10.02	1.28	0.80	26.33
96	1.74	0.11	17.03	1.37	0.86	29.20
97	1.89	0.26	21.81	1.52	0.93	36.21
98	1.93	0.36	25.60	1.62	1.12	37.85
99	1.95	0.71	28.15	1.82	1.31	39.27

Table 5 (continued)

This table presents the values of t -statistics at selected percentiles (%) of the distribution of t -statistics of the actual and simulated abnormal returns, as well as the percentage of the 5000 simulation runs that produce lower values of t -statistics at the selected percentiles than those actual abnormal returns (% simulated < actual) for the *upgrade* and *downgrade* portfolios, using the subsample of UK sell-side analyst recommendation revisions made by the top 5 brokerage houses from January 1996 to June 2013. The abnormal gross return is estimated as the intercept term derived from the Fama and French (2015) five-factor model. The abnormal net return is calculated as the abnormal gross return less the estimated single-trip transaction costs for purchasing stocks at 0.75% and for short selling those at 1.5%, multiplied by the corresponding average daily portfolio turnover. The top 5 brokerage houses are identified by their 3-year moving average ($t-3$, $t-2$, $t-1$) of positions on the annual All-Europe Research Team published by *Institutional Investor* (see “Appendix 1”)

that, for the *upgrade* portfolio, the actual t -statistics are always smaller than the average values from the simulations for all percentiles within both industry sectors, suggesting sell-side analysts’ lack of skill in making valuable upward revisions over the whole sample period.

In contrast, for the *downgrade* portfolio within Health Care sector, the right tails of the CDFs of the actual t -statistics suggest that there are superior sell-side analysts who can make valuable downgrades after transaction costs over some periods of time. For example, the right side of Panel A shows that the CDF of the actual t -statistics of the abnormal net returns moves to the right tail of the average from the simulations at about the 80th percentile. The 95th percentile of t -statistics averages 0.79 for the simulations, but the actual 95th percentile of t -statistics is higher, 1.24. Similarly, for the *downgrade* portfolio within Technology sector, the crossover occurs at the higher percentile (around the 70th), suggesting that sell-side analysts do possess sufficient skill in making valuable downgrades for stocks with high-tech related characteristics over some periods of time, even after transaction costs. Figures 8a, b illustrate the CDFs of the actual t -statistics of the abnormal net returns and the corresponding average simulated CDFs for the *downgrade* portfolio, within the industry sector of Health Care (Technology).

5 Conclusions

The purpose of this inquiry is to conduct an in-depth investigation into the investment value of sell-side analyst recommendation revisions in the UK from January 1995 to June 2013, using a uniquely insightful database that has never been examined before. We take an investor-oriented, calendar-time perspective, to assess the time-varying performance of the *upgrade* and *downgrade* portfolios. Our empirical investigation shows that, on average, sell-side analysts’ upward revisions are valueless over the whole sample period; it is likely for investors to make profits by short selling stocks with downward revisions (before transaction costs) over some periods of time, while these profits disappear after transaction costs. Our results do not alter when we construct two alternative *upgrade* and *downgrade* portfolios exclusively using a subsample of analyst recommendation revisions made by the top 5 brokerage houses. This suggests that the reputation of brokerage houses does not play an important role in making valuable analyst recommendation revisions in the

Table 6 Percentiles of *t*-statistics for actual and simulated abnormal net returns under the Fama and French (2015) five-factor model, within two industry sectors of Health Care (ICB 45) and Technology (ICB 95)

%	Upgrade portfolio			Downgrade portfolio		
	Simulated <i>t</i> -stat	Actual <i>t</i> -stat	% (simulated < actual)	Simulated <i>t</i> -stat	Actual <i>t</i> -stat	% (simulated < actual)
Panel A: abnormal net returns within Health Care (ICB 45) sector						
1	-2.49	-3.69	0.03	-2.68	-3.41	3.19
2	-2.17	-3.36	0.04	-2.23	-2.98	3.01
3	-1.98	-3.13	0.06	-1.95	-2.72	3.42
4	-1.84	-3.00	0.06	-1.78	-2.51	4.16
5	-1.73	-2.87	0.06	-1.68	-2.39	5.19
10	-1.35	-2.54	0.06	-1.38	-1.89	8.53
20	-0.88	-2.01	0.07	-1.03	-1.45	11.69
30	-0.55	-1.58	0.09	-0.77	-1.15	21.29
40	-0.26	-1.20	0.11	-0.57	-0.93	27.31
50	0.01	-0.87	0.12	-0.41	-0.71	35.14
60	0.27	-0.51	0.17	-0.26	-0.51	43.22
70	0.57	-0.18	0.21	-0.11	-0.28	54.26
80	0.91	0.19	0.39	0.08	0.01	60.28
90	1.38	0.88	6.10	0.41	0.56	74.62
95	1.77	1.35	12.08	0.79	1.24	80.30
96	1.89	1.49	14.54	0.93	1.38	84.60
97	2.03	1.61	16.00	1.10	1.61	87.67
98	2.22	1.81	24.02	1.36	1.89	93.82
99	2.52	1.87	34.64	1.81	1.92	95.46
Panel B: abnormal net returns within Technology (ICB 95) sector						
1	-3.07	-3.73	0.06	-2.69	-3.30	1.74
2	-2.50	-3.42	0.07	-2.25	-2.64	4.36
3	-2.20	-3.17	0.08	-1.98	-2.39	4.55
4	-2.05	-2.90	0.10	-1.81	-2.22	6.46
5	-1.93	-2.71	0.10	-1.69	-2.11	7.12
10	-1.48	-2.17	0.11	-1.39	-1.73	7.70
20	-0.99	-1.69	0.13	-1.15	-1.35	8.77
30	-0.62	-1.32	0.16	-1.06	-1.20	9.65
40	-0.30	-1.03	0.22	-1.02	-1.12	14.12
50	-0.01	-0.75	0.25	-1.01	-1.07	16.48
60	0.29	-0.46	0.30	-0.99	-1.03	25.75
70	0.57	-0.13	0.31	-0.98	-0.98	54.93
80	0.91	0.29	0.62	-0.95	-0.88	56.24
90	1.38	0.90	5.02	-0.85	-0.73	66.68
95	1.79	1.33	8.14	-0.73	-0.60	73.57
96	1.90	1.44	10.40	-0.69	-0.55	78.85
97	2.04	1.62	12.31	-0.61	-0.47	85.59
98	2.24	1.82	14.79	-0.47	-0.32	92.15
99	2.75	1.84	24.27	-0.15	-0.05	96.24

Table 6 (continued)

This table presents the values of t -statistics at selected percentiles (%) of the distribution of t -statistics of the actual and simulated abnormal returns, as well as the percentage of the 5000 simulation runs that produce lower values of t -statistics at the selected percentiles than those actual abnormal returns for the *upgrade* and *downgrade* portfolios, using the subsample of UK sell-side analyst recommendation revisions within two high-tech industry sectors, i.e., Health Care (ICB 45 in Panel A) and Technology (ICB 95 in Panel B) sectors, identified by the two-digit ICB codes (see “Appendix 2”), from January 1996 to June 2013. The abnormal net return is calculated as the abnormal gross return, which is estimated as the intercept term derived from the Fama and French (2015) five-factor model, less the estimated single-trip transaction costs for purchasing stocks at 0.75% and for short selling those at 1.5%, multiplied by the corresponding average daily portfolio turnover

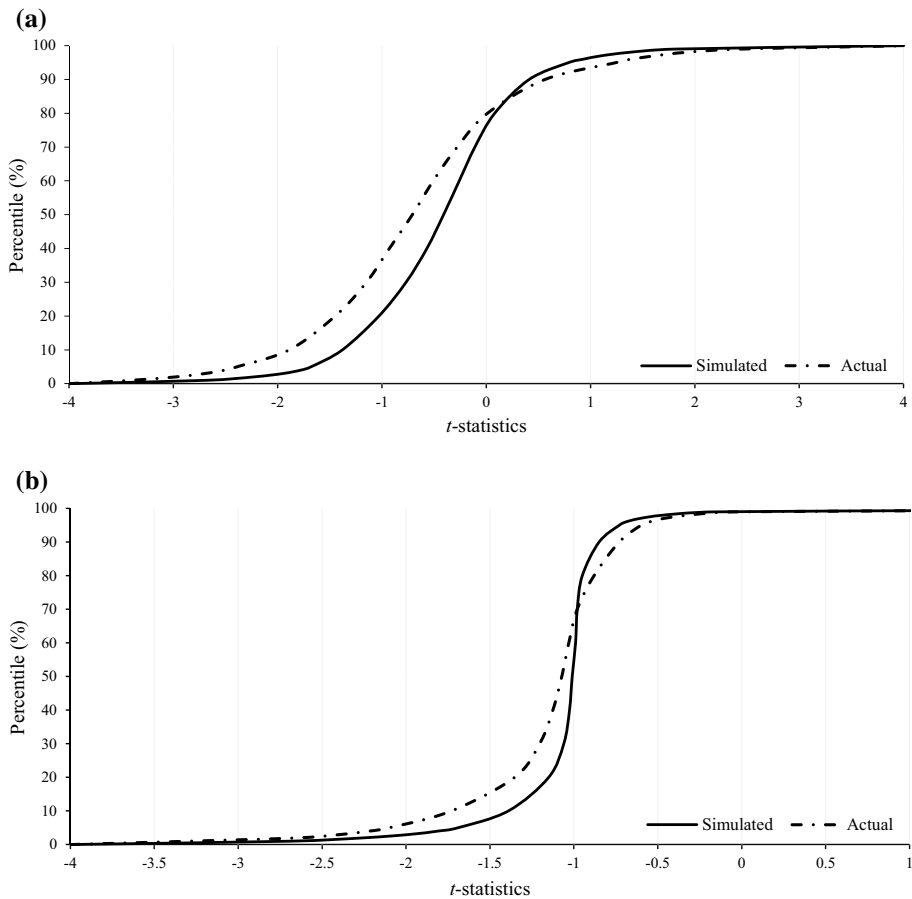


Fig. 8 Simulated and actual cumulative density function (CDF) of t -statistics for the abnormal net returns to the *downgrade* portfolio, under the Fama and French (2015) five-factor model, within **a** Health Care (ICB 45) sector and **b** Technology (ICB 95) sector

UK, inconsistent with that reported in the US. One possible explanation on the discrepancy could be that the annual All-European Research Team published by *Institutional Investor* has less influence on UK sell-side analysts' career concern, compared with the influence of its US counterpart. Further research might focus on the development of more appropriate proxies for the reputation of brokerage houses and sell-side analysts in the UK (see, e.g., Nolte et al. 2014).

However, our industry-based analysis shows that, within two high-tech industry sectors, i.e., Health Care (ICB 45) and Technology (ICB 95) sectors, the *downgrade* portfolio generates significantly negative abnormal net returns in several periods of time. These significantly negative abnormal net returns suggest the importance of controlling for industry in sell-side analyst research. From an investor's perspective, it is likely to make large enough profits to cover the size of transaction costs by short selling stocks with downward revisions with high-tech related characteristics over some periods of time.

Our *time-series* bootstrapping simulations confirm that, on average, (1) the observed insignificantly positive abnormal returns (both gross and net of transaction costs) to the *upgrade* portfolio could be attributed to sell-side analysts' lack of skill in making valuable upward revisions, rather than their bad luck; and (2) sell-side analysts have certain skill in making valuable downward revisions over some periods of time (at least before transaction costs), though such skill is not sufficient to cover the size of transaction costs. More importantly, our simulated results confirm that sell-side analysts do possess superior skill in making valuable downward revisions for stocks with high-tech related characteristics, even after transaction costs are taken into account.

Finally, it is worth mentioning that there is some slight differences between the investment value and profitability of sell-side analyst recommendations.¹⁵ On the one hand, analyst recommendations could be worthless, but the portfolio might be profitable. For example, Green (2006) reports that early access to stock recommendations provides investors with incremental investment value, which could be attributed to the existence of *momentum traders* in the market (Hong and Stein 1999). These *momentum traders* have a tendency to exchange aggressively and deviate a stock's price beyond its fundamental value, thus leading to a market overreaction in the short term. On the other hand, analyst recommendations are in fact valuable, but the portfolio might end up not being profitable, probably due to the *crowd* effect when the information is widely and publicly broadcast. According to Hong and Stein (1999), the market firstly underreacts to the release of analyst recommendations, as *news watchers* tend to react to information with a delay. The initial underreaction is generally followed by overreaction, since investors may chase fad, which drives stock prices overshoot their long-term equilibrium, and eventually causes the portfolio not profitable in the long term. In this manner, the key implication of the Hong and Stein (1999) model on sell-side analyst research is the speed of reaction to stock recommendations (Green 2006; Jegadeesh and Kim 2006), which could be left for future research.

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¹⁵ We thank an anonymous reviewer for pointing out the difference between the investment value and profitability of sell-side analyst recommendations.

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Appendix 1: The top 5 brokerage houses

Ranking	Brokerage houses	Ranking	Brokerage houses
1996		1997	
1	SBC Warburg Securities (1, 1, 1)	1	SBC Warburg (1, 1, 1)
2	James Capel and Co. (2, 2, 2)	2	James Capel and Co. (2, 2, 2)
3	Barclays de Zoete Wedd (BZW) (4, 3, 3)	3	BZW (3, 3, 6)
4	NatWest Securities (5, 5, 5)	4	NatWest Securities (5, 5, 5)
5	UBS (2, 6, 8)	5	UBS (6, 8, 3)
1998		1999	
1	SBC Warburg Dillion Read (1, 1, 1)	1	Warburg Dillion Read (1, 1, 1)
2	HSBC James Capel (2, 2, 5)	2	UBS (3, 2, 3)
3	UBS (8, 3, 2)	3	Merrill Lynch (4, 3, 2)
4	NatWest Securities (5, 5, 4)	4	NatWest Securities (5, 4, 4)
5	BZM (3, 6, 6)	5	HSBC James Capel (2, 5, 9)
2000		2001	
1	Warburg Dillion Read (1, 1, 2)	1	Merrill Lynch (2, 1, 1)
2	Merrill Lynch (3, 2, 1)	2	Warburg Dillion Read (1, 2, 3)
3	Goldman Sachs International (7, 5, 4)	3	Goldman Sachs International (5, 4, 6)
4	HSBC Securities (5, 9, 8)	4	Morgan Stanley Dean Witter (11, 3, 2)
5	Morgan Stanley Dean Witter (9, 11, 3)	5	Credit Suisse First Boston (12, 6, 4); Deutsche Bank (9, 8, 5)
2002		2003	
1	Merrill Lynch (1, 1, 2)	1	Credit Suisse First Boston (4, 1, 2)
2	UBS Warburg (2, 3, 4)	2	UBS Warburg (3, 4, 1)
3	Morgan Stanley Dean Witter (3, 2, 5)	2	Merrill Lynch (1, 2, 5)
4	Credit Suisse First Boston (6, 4, 1)	4	Deutsche Bank (5, 3, 3)
5	Deutsche Bank (8, 5, 3)	5	Morgan Stanley (2, 5, 6)
2004		2005	
1	UBS Warburg (4, 1, 1)	1	UBS (1, 1, 1)
2	Credit Suisse First Boston (1, 2, 4)	2	Smith Barney Citigroup (4, 2, 2)
3	Deutsche Bank (3, 3, 3)	3	Credit Suisse First Boston (2, 4, 3)
4	Citigroup/Schroder Salomon Smith Barney (6, 4, 2)	4	Deutsche Bank (3, 3, 5)
4	Merrill Lynch (2, 5, 5)	5	Merrill Lynch (5, 5, 3)
2006		2007	
1	UBS (1, 1, 1)	1	UBS (1, 1, 1)
2	Smith Barney Citigroup (2, 2, 4)	2	Citigroup (2, 4, 2)
3	Deutsche Bank (3, 5, 2)	3	Deutsche Bank (5, 2, 3)
4	Merrill Lynch (5, 3, 3)	4	Merrill Lynch (3, 3, 5)
5	Credit Suisse First Boston (4, 3, 6)	5	Credit Suisse (3, 6, 5)

Ranking	Brokerage houses	Ranking	Brokerage houses
2008		2009	
1	UBS (1, 1, 1)	1	UBS (1, 1, 1)
2	Citigroup (4, 2, 2)	2	Citi Investment Research (2, 2, 2)
3	Deutsche Bank (2, 3, 5)	3	Merrill Lynch (5, 3, 3)
4	Merrill Lynch (3, 5, 3)	4	Credit Suisse (5, 4, 4)
5	Credit Suisse (6, 5, 4)	5	Deutsche Bank (3, 5, 7)
2010		2011	
1	UBS (1, 1, 1)	1	UBS (1, 1, 1)
2	Citi (2, 2, 3)	2	BofA Merrill Lynch Global Research (3, 2, 5)
3	Bank of America Securities-Merrill Lynch (3, 3, 2)	2	Credit Suisse (4, 5, 2)
4	Credit Suisse (4, 4, 5)	2	Citi (2, 3, 8)
5	Morgan Stanley (7, 5, 5)	5	J.P. Morgan (8, 4, 2)
2012		2013	
1	UBS (1, 1, 2)	1	UBS (1, 2, 2)
2	J.P. Morgan Cazenove (4, 2, 4)	2	Deutsche Bank (6, 1, 1)
2	BofA Merrill Lynch Global Research (2, 5, 3)	3	BofA Merrill Lynch Global Research (5, 3, 2)
4	Credit Suisse (5, 2, 4)	3	J.P. Morgan Cazenove (2, 4, 4)
5	Deutsche Bank (7, 6, 1)	5	Credit Suisse (2, 4, 6)

This appendix provides a list of the top 5 brokerage houses based on their 3-year moving average of positions on the annual All-Europe Research Team published by *Institutional Investor* from 1996 to 2013. For each brokerage house in each year of t , its positions in previous 3 years ($t-3$, $t-2$, $t-1$) are shown in bracket. For example, the ranking of each brokerage house in the calendar year of 1996 is determined based on its average position in the years of 1995, 1994, and 1993

Appendix 2: Distribution of UK analyst recommendation revisions in the *upgrade* and *downgrade* portfolios by industry sectors of the covered firms

Two-digit ICB codes	Three-digit ICB codes	Upgrade portfolio				Downgrade portfolio			
		No. of covered firms	No. of brokerage houses	Average rating	No. of upward revisions	No. of covered firms	No. of brokerage houses	Average rating	No. of downward revisions
05 Oil and Gas	053 Oil and Gas Producers	58	55	2.21 [1.23]	746	66	59	6.10 [3.66]	798
	057 Oil Equipment, Services, and Distribution	18	39	2.29 [1.27]	269	18	41	5.73 [3.44]	266
	058 Alternative Energy	8	16	2.14 [1.14]	35	5	14	5.32 [3.20]	25

Two-digit ICB codes	Three-digit ICB codes	<i>Upgrade</i> portfolio				<i>Downgrade</i> portfolio			
		No. of covered firms	No. of broker- age houses	Average rating	No. of upward revis- ions	No. of covered firms	No. of broker- age houses	Average rating	No. of down- ward revisions
13 Chemi- cals	135 Chemi- cals	39	52	2.25 [1.24]	701	40	54	5.69 [3.44]	763
17 Basic Resources	173 Forestry and Paper	4	13	2.31 [1.31]	32	4	15	6.07 [3.67]	43
	175 Industrial Metals and Mining	8	24	2.23 [1.25]	53	11	31	6.51 [3.96]	111
	177 Mining	62	46	2.19 [1.21]	536	57	47	5.99 [3.62]	613
23 Construc- tion and Materials	235 Construc- tion and Materi- als	66	52	2.31 [1.26]	929	64	57	5.98 [3.61]	1022
27 Industrial Goods and Services	271 Aero- space and Defence	17	49	2.30 [1.28]	584	17	48	5.72 [3.44]	514
	272 General Industrials	18	44	2.23 [1.25]	400	19	50	5.79 [3.48]	492
	273 Elec- tronic and Electrical Equipment	66	46	2.30 [1.27]	602	73	53	5.69 [3.42]	691
	275 Industrial Engineer- ing	77	50	2.29 [1.26]	976	83	57	5.67 [3.41]	1053
	277 Industrial Transporta- tion	39	49	2.25 [1.24]	489	42	54	5.87 [3.55]	596
	279 Support Services	221	67	2.25 [1.24]	2757	236	73	5.85 [3.53]	3019
	335 Automot- iles and Parts	14	34	2.28 [1.26]	184	18	41	5.89 [3.56]	245
35 Food and Beverage	353 Bever- ages	14	42	2.27 [1.25]	293	15	48	6.17 [3.75]	415
	357 Food Producers	46	46	2.24 [1.25]	788	52	49	5.86 [3.54]	981
37 Personal and Household Goods	372 House- hold Goods and Home Construc- tion	57	52	2.33 [1.26]	962	62	56	5.94 [3.59]	1105
	374 Leisure Goods	16	29	2.33 [1.25]	135	18	33	5.77 [3.47]	158
	376 Personal Goods	39	38	2.32 [1.24]	260	46	43	5.66 [3.42]	302
	378 Tobacco	3	18	2.09 [1.15]	94	3	19	5.91 [3.58]	100

Two-digit ICB codes	Three-digit ICB codes	<i>Upgrade</i> portfolio				<i>Downgrade</i> portfolio			
		No. of covered firms	No. of broker- age houses	Average rating	No. of upward revi- sions	No. of covered firms	No. of broker- age houses	Average rating	No. of down- ward revisions
45 Health Care	453 Health Care Equip- ment and Services	39	49	2.23 [1.22]	392	46	52	5.72 [3.44]	480
	457 Pharma- ceuticals and Bio- technology	64	57	2.24 [1.23]	556	68	57	5.91 [3.57]	681
53 Retail	533 Food and Drug Retailers	20	51	2.25 [1.24]	562	22	53	6.41 [3.88]	906
	537 General Retailers	110	63	2.28 [1.25]	2220	121	68	6.14 [3.71]	3099
55 Media	555 Media	130	65	2.22 [1.22]	1252	139	64	5.73 [3.46]	1375
57 Travel and Leisure	575 Travel and Leisure	143	66	2.20 [1.19]	2462	149	69	5.88 [3.55]	2944
65 Telecom- munica- tions	653 Fixed Line Tel- ecommu- nications	21	47	2.14 [1.16]	219	20	48	6.07 [3.66]	274
	657 Mobile Telecom- munications	11	37	2.12 [1.14]	99	13	33	5.82 [3.53]	89
75 Utilities	753 Electric- ity	13	35	2.16 [1.19]	186	12	33	6.08 [3.69]	247
	757 Gas, Water, and Multiutili- ties	19	35	2.22 [1.24]	365	17	35	5.97 [3.60]	419
83 Banks	835 Banks	14	48	2.23 [1.23]	606	15	47	6.32 [3.84]	806
85 Insurance	853 Nonlife Insurance	47	43	2.33 [1.33]	701	47	46	5.81 [3.50]	703
	857 Life Insurance	13	36	2.24 [1.23]	266	15	37	6.01 [3.64]	296
87 Financial Services	873 Real Estate	85	47	2.30 [1.30]	827	85	50	5.83 [3.50]	875
	877 General Financial	128	61	2.25 [1.24]	1346	130	64	5.86 [3.53]	1501
95 Technol- ogy	953 Soft- ware and Computer Services	169	66	2.19 [1.18]	1356	189	69	5.94 [3.59]	1764
	957 Technol- ogy Hard- ware and Equipment	42	54	2.12 [1.13]	461	44	54	6.10 [3.69]	603

Two-digit ICB codes	Three-digit ICB codes	Upgrade portfolio				Downgrade portfolio			
		No. of covered firms	No. of broker- age houses	Average rating	No. of upward revi- sions	No. of covered firms	No. of broker- age houses	Average rating	No. of down- ward revisions
Overall		1958	111	2.25 [1.24]	25,701	2081	109	5.93 [3.58]	30,374

This appendix presents the distribution of 25,701 upward (30,374 downward) changes in analyst recommendations in the *upgrade* (*downgrade*) portfolio from January 1993 to June 2013 by industry sectors of the recommended firms, in terms of the number of firms covered, the number of brokerage houses, as well as the average rating and number of analyst recommendation revisions. All real-time analyst recommendations are obtained from *Morningstar Company Intelligence*. A rating of 1 reflects a strong buy, 2 a buy, 3 a weak buy, 4 a weak buy/hold, 5 a hold, 6 a hold/sell, 7 a weak sell, 8 a sell, and 9 a strong sell, which are reclassified into five categories: Strong Buy (1 and 2), Buy (3 and 4), Hold (5), Sell (6 and 7), and Strong Sell (8 and 9). An *upgrade* portfolio consists of all stocks with upward revisions to Strong buys or Buys from previous Strong Sells, Sells, or Holds, while a *downgrade* portfolio consists of all stocks with downward revisions to Strong Sells, Sells, or Holds from previous Strong Buys or Buys. We report the average rating for analyst recommendation revisions based on the nine-point rating scale, while in square brackets, we report the average rating based on the five-point rating scale

Appendix 3: Time-series bootstrapping simulation method

This appendix illustrates the rolling window-based *time-series* bootstrapping simulation method with the Fama and French (2015) five-factor model, but the application of the bootstrapping procedure to the CAPM, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model is very similar, with the only modification of the following steps being the substitution of appropriate asset pricing models (see, Su and Zhang 2018).

First, in the first 1-year rolling window (January 3, 1995 to December 29, 1995), we estimate the Fama and French (2015) five-factor model to calculate the estimated alphas, factor loadings, and residuals using the time series of daily excess returns for the portfolio, $\{(R_{p,t} - R_{f,t}), t = T_{p,1}, \dots, T_{p,252}\}$, where $T_{p,1}$ and $T_{p,252}$ are the first and last trading dates, respectively, in the rolling window:

$$R_{p,t} - R_{f,t} = \hat{\alpha}_p + \hat{\beta}_p(R_{m,t} - R_{f,t}) + \hat{\delta}_p SMB_t + \hat{h}_p HML_t + \hat{r}_p RMW_t + \hat{c}_p CMA_t + \hat{\varepsilon}_{p,t}. \quad (9)$$

Second, we save the coefficient estimates, $\{\hat{\alpha}_p, \hat{\beta}_p, \hat{\delta}_p, \hat{h}_p, \hat{r}_p, \hat{c}_p\}$, the time series of estimated residuals, $\{\hat{\varepsilon}_{p,t}, t = T_{p,1}, \dots, T_{p,252}\}$, and the t -statistic of alpha, $\hat{t}_{\hat{\alpha}_p}$.

Third, we generate a pseudo-time series of resampled residuals $\{\hat{\varepsilon}_{p,t_b}^b, t_b = T_{p,1}^b, \dots, T_{p,252}^b\}$ by randomly drawing residuals from the saved residual vector $\{\hat{\varepsilon}_{p,t}\}$ with replacements, where b is the bootstrapping simulation index. In the same way, we generate a pseudo-time series of risk factors $\{(R_{m,t_b} - R_{f,t_b})^b, SMB_{t_b}^b, HML_{t_b}^b, RMW_{t_b}^b, CMA_{t_b}^b\}$ by randomly drawing risk factors from the original risk factor vector $\{(R_{m,t} - R_{f,t}), SMB_t, HML_t, RMW_t, CMA_t\}$ with replacements.

Fourth, we generate a time series of pseudo-daily excess returns $(R_{p,t} - R_{f,t})^b$ in the rolling window, imposing the null hypothesis of zero true performance ($\alpha_p = 0$):

$$\left\{ (R_{p,t} - R_{f,t})^b = 0 + \hat{\beta}_p (R_{m,t_b} - R_{f,t_b})^b + \hat{s}_p SMB_{t_b}^b + \hat{h}_p HML_{t_b}^b + \hat{r}_p RMW_{t_b}^b + \hat{c}_p CMA_{t_b}^b + \hat{\varepsilon}_{p,t_b}^b \right\} \quad (10)$$

where $t = T_{p,1}, \dots, T_{p,252}$; $t_b = T_{p,1}^b, \dots, T_{p,252}^b$.

Finally, we regress the pseudo-daily excess returns $(R_{p,t} - R_{f,t})^b$ on the five factors:

$$(R_{p,t} - R_{f,t})^b = \hat{\alpha}_p^b + \hat{\beta}_p (R_{m,t} - R_{f,t}) + \hat{s}_p SMB_t + \hat{h}_p HML_t + \hat{r}_p RMW_t + \hat{c}_p CMA_t + \hat{\varepsilon}_{p,t} \quad (11)$$

The simulated $\hat{\alpha}_p^b$ represents the sampling variation around zero true performance, entirely due to random chance (luck). Repeating the above steps in each of the 4420 rolling windows from January 1996 to June 2013, we obtain a time series of simulated alphas, $\{\hat{\alpha}_p^b\}$, and their corresponding t -statistics, $\{\hat{t}_{\hat{\alpha}_p^b}\}$. We then order all simulated $\hat{\alpha}_p^b$ into a cumulative distribution function (CDF) of simulated $\hat{\alpha}_p^b$ —a separate time series of *luck* distribution from the worst performing rolling window to the best performing rolling window, all of which are completely due to sell-side analysts' luck rather than their skill. We repeat the above bootstrapping simulation a large number of times, say, $b = 1, \dots, 5000$.

Note that our approach measures the performance distribution of the best performing rolling windows not just by resampling from distribution of the *ex-post* best performing rolling windows, but using the information about *luck* represented by *all* rolling windows. This is a major difference between our approach and those employed in prior studies, as they generally ignore the possibility that luck distribution encountered by all other performance distributions also provides highly valuable and relevant information (see, White 2000; Cuthbertson et al. 2008).

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