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Essays in Empirical Finance

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Essays in Empirical Finance

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of the requirements for the degree
Doctor of Philosophy in Management

by

Aurelien Philippot

2015

Abstract of the Dissertation

Essays in Empirical Finance

by

Aurelien Philippot
Doctor of Philosophy in Management
University of California, Los Angeles, 2015
Professor Mark J. Garmaise, Chair

My dissertation has two chapters. The first chapter is titled "Analysts' reinititations of coverage and market underreaction". I study a signal which has been completely ignored by the literature so far: reinitiations of coverage. Reinitiations are defined as the resumption of coverage of a stock by a broker after more than six months of interruption. They are associated with a significant short-term market response, in particular when the same analyst is assigned to the stock. However, this market response is incomplete. Interestingly, the price patterns that follow the issuance of regular upgrades of recommendation and reinitiations differ significantly, and this paper can help us better understand the phenomena of market underreaction and overreaction. Prices adjust quickly after a regular upgrade, while reinitiations are followed by a sustained price increase in the following six months. I assess the economic magnitude of this initial underreaction by setting up a trading strategy. Reinitiations of coverage are the only type of recommendation that delivers significant positive abnormal returns after transaction costs with a three- and six-month investment horizon. I investigate several explanations in relation to gradual information diffusion, limited attention and changes in firm profitability. Portfolio sorts on proxies for market attention indicate that firms subject to a lower level of initial attention experience the strongest cumulative abnormal returns. Reinitiations also coincide with improvements in firms' profitability.

The second chapter is co-authored with Ivo I. Welch and is titled "Are Economic Tracking Portfolios (ETP) useful? And What Fundamentals Are Driving Stock Prices?". Our paper shows that equity-based economic tracking portfolios ([BGL89], [Lam01]) constructed from

the ten Fama-French industry equity portfolios and three bond portfolios could not usefully track selected macro-series (inflation, industrial production growth, consumption, real estate, exchange rates, and oil) any better than simpler benchmarks (a constant, the T-bill, the S&P500, and/or a single stock). This suggests that the in-sample ability of ETPs to track macro-series was likely just overfitting. In most cases, the zero constant and/or Treasury Bill tracked best. This reinforces perhaps the most fundamental mystery in finance: what economic variables, if any, are really driving stock prices ([Rol88])?

The dissertation of Aurelien Philippot is approved.

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2015

“Ne deviens pas esclave du jugement des hommes; sinon tu périras comme les gladiateurs de Rome” Daniel Desbiens

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CHAPTER 1

Analysts' reinitiations of coverage and market underreaction

1.1 Introduction

Whether sell-side analysts add value has been a debate for many years among financial economists. Analysts gather and collect pieces of information about the firm fundamentals, and produce forecasts and ratings. Previous work has documented that the release of analysts' reports is associated with abnormal returns. For example, [Sti95] shows that buy recommendations are followed by an average abnormal return of 1.2% in the eleven business days centered on the issuance day, and [Wom96] documents an abnormal return of 3% in the three-day period surrounding the addition of a stock to the buy list of a broker. However, it is unclear to what extent investors can actually benefit from following analysts' advice. For example, according to [BLM01], strategies based on purchasing stocks that have the most favorable recommendations are unlikely to generate abnormal returns that survive transaction costs.

In this paper, I focus on reinitiations of coverage. I define a reinitiation of coverage as the first report issued by an analyst after a period of interruption of at least six months. Several reasons can lead a broker to discontinue the coverage of a firm: the analyst might have left the broker, the stock might have been placed on a restricted list because of regulatory requirements, or the analyst might believe that the firm's prospects are poor. The latter is reflected in [MO97] self-selection hypothesis. Analysts would prefer to stop the coverage of a firm rather than downgrade it and potentially damage their relationship with its management. In a similar vein, [Sch08] argues that terminations of coverage enable analysts to withhold bad news about the firms they cover. [KL07] find that exogenous terminations of coverage [1] carry no information about the future performance of the covered firms, unlike a control group of endogenous terminations. I filter out resumptions of coverage that are less than six months old in order to remove terminations of coverage that are motivated by regulatory or other exogenous reasons.

In line with previous studies, I consider both rating levels and changes. Indeed, [Wom96] documents that upgrades lead to the strongest short-term response, and [JKK04] find that recommendations changes have a stronger predictive power than recommendation levels. I call a reinitiation upgrade, a reinitiation issued with a higher rating than the last rating known before the discontinuation. Reinitiation upgrades lead to a stronger short-term market reaction than reinitiations with positive rating [2] (2.31% two-day cumulative abnormal return versus 1.70%). This initial market response is similar to the one that follows regular upgrades.

Interestingly, I also find a significant delayed price reaction and document the existence of a six-month drift after a reinitiation announcement (cumulative abnormal returns of 3.31% for reinitiation upgrades). This result sharply differentiates reinitiations of coverage from regular upgrades: indeed, even though regular upgrades are followed by an immediate market response of the same magnitude as reinitiations, the asset pricing implications of upgrades are short lived and the price adjustment is relatively quick (cumulative abnormal returns are zero after three months and even become negative after six months). On the other hand, the valuation effect that follows reinitiations does not revert over the horizon of my study.

I investigate the economic relevance of this anomaly by testing whether a profitable investment strategy can be implemented with these recommendations. I form calendar-time

[1] In their paper, exogenous terminations correspond to a broker's decision to terminate the coverage of a whole sector, or the closure of a brokerage house.

[2] Positive reinitiations come with a rating of buy of strong buy

portfolios and design a trading strategy that incorporates transaction costs, estimated from the algorithm developed by [CS12]. With a three-month horizon, investing in reinitiations by the same analyst produces an average monthly abnormal return of 0.55%, and investing in reinitiation upgrades by the same analyst generates an average monthly abnormal return of 0.64%. Both are significantly greater than zero and strictly dominate the monthly abnormal returns that come from initiations of coverage or regular upgrades (both of which are not different from 0). Similar results still hold when I use a six-month investment horizon. This is another interesting contribution of this paper that contrasts with the previous literature.

Gradual information diffusion models among heterogeneous agents like [HS99] have been proposed to explain the existence of market underreaction, and [HLS00] found supporting empirical evidence to explain momentum. In this paper, I take a closer look at several candidate explanations. Limited attention has sometimes been suggested to account for anomalies like the post-earnings announcement drift. It relies on the idea that attention is a scarce resource or that agents become aware of a signal only after it crosses their perception filters. For example, limited attention has been used in several theoretical models to explain underreaction to public accounting information when investors are risk-averse and a group of investors neglects a piece of information about future profitability contained in the latest earnings announcement ([DP09]), or to show why information is incorporated faster in large stocks than in small stocks ([Pen05]). Reinitiations of coverage are not a very frequent signal, and the stock market is flooded with other signals that look quite similar but are actually meaningless (for example, in the data, many analysts suspend the coverage of a firm only to resume it a few days later). With multiple firm announcements disclosed simultaneously, market participants face a daunting processing task given their finite attention capacity. [Sim71] explains the challenge very well: "the wealth of information means the dearth of something else: a scarcity of whatever it is that information consumes. What information it consumes is rather obvious: it consumes the attention of its recipients. Hence, a wealth of information creates a poverty of attention". Let alone the fact that it is certainly more difficult for small investors to spend the time and effort to separate the wheat from the chaff.

I directly test the comparative static implications of limited attention models by picking two usual proxies for investor attention: turnover and analyst coverage. I estimate the average daily turnover in the three months that precede the discontinuation of coverage, allocate each stock to five portfolios, and compute the change in turnover between the pre-discontinuation and post-reinitiation periods: stocks with a smaller initial turnover are subject to a significantly stronger increase in turnover after the reinitiation is issued. This is consistent with the idea that reinitiations of coverage are coincidental with an increase and perhaps a renewed market interest for these stocks that had lost some coverage. In addition, stocks that are in the two portfolios with the lowest initial turnover generate the strongest cumulative abnormal returns in the three months after the reinitiation is issued. As a robustness check, I allocate firms to portfolios based on the pre-reinitiation level of analyst coverage. Results are weaker but still indicate that a lower level of coverage is followed by stronger cumulative abnormal returns. Thus, limited attention could partially explain a slow adjustment to the announcement of reinitiations of coverage by the same analyst.

Furthermore, it is worth keeping in mind why reinitiations could be expected to contain positive information about the firms: an analyst who decides to resume the coverage of a stock not only benefits from his prior knowledge of the company and its management but he also has the option to time the release of his report. Therefore, I expect reinitiations of coverage with a positive rating to be associated not only with a strong stock market performance but also with an improvement in the firms' operating performance. I look at the change in operating performance (measured by the industry adjusted return on asset and EBIT margin). The profitability of firms subject to reinitiations by the same analyst and reinitiation upgrades by the same analyst increases significantly both on the year the reinitiation takes place and in the following year. On the other hand, the profitability of firms subject to regular upgrades goes down each year. This result suggests that analysts who reinitiate the coverage of a firm have the ability to select firms with better future operating performance. The improvement in profitability could partially explain the persistent valuation effect for reinitiations.

The rest of the paper proceeds as follows: Section 1.2 describes the data and defines the different types of recommendations that are studied. Section 1.3 describes the results of the short-term event study and the univariate tests. Section 1.4 documents the market underreaction related to reinitiations and the existence of a drift. Section 1.5 implements the trading strategies. Section 1.6 explores different possible explanations (limited attention and improvement in operating performance) and Section 1.7 concludes.

1.2 Data

Recommendations come from IBES and cover the period 2003-June 2013. [3] I keep US Firms only and link IBES to CRSP. As shown in [BLM06], the enactment of NASD Rule 2711 in 2002, which required the public dissemination of ratings distribution was accompanied by ratings distribution changes. Many brokers switched from a five-point to a three-point ratings scale and stopped their recommendations before resuming them under their new scale during the spring and summer of 2002. I deal with this structural break by requiring the stopped recommendation that precedes the reinitiation to be posterior to January 1, 2003. In addition, it should be easier to identify reinitiations of coverage in the post-settlement period because brokers have been asked to release specific reports when they stop the coverage of a firm.[4] Indeed, NYSE Rule 472(f)(6) states that: "if a member or member organization intends to terminate its research coverage of a subject company, notice of this termination

[3] [LMM09] compared several vintages of the IBES database and found that some analyst records had been modified a posteriori. About one third of the observed differences were anonymizations that were subsequently corrected by IBES. Another third of the differences across vintages were coming from two specific brokers on Canadian and non US firms (in my paper, I focus on US firms, which protects me from that issue). Finally, about one third of the observed differences came from additions (the more recent tape having more observations than the older one). As a response to the paper, IBES has spent effort to correct the database from these biases, as explained by [LMM09]:"Thomson is now planning to produce a true 'as-was' historical recommendations database in response to our investigation. This should allow future researchers to consistently and accurately replicate any analysis that employs historical recommendations data". The vintage I use should reflect these improvements.

[4] IBES also makes sure that recommendations are up to date and contacts an analyst who has not updated a recommendation for 180 days to make sure he still covers the stock.

must be made. The member or member organization must make available a final research report on the subject company using the means of dissemination equivalent to those it ordinarily uses to provide the customer with its research reports on the subject company". The broker should also either give a final rating or if not, justify the decision to terminate coverage.[5]

I define a reinitiation of coverage as the first recommendation issued by a broker after a discontinuation of at least six months. I pick the six-month threshold in order to eliminate several situations: first, a broker sometimes has to place a stock on a restricted list because of an existing underwriting relationship. In that case, the broker is likely to resume the coverage at the end of the restriction period. Second, it is not uncommon for analysts to stop the coverage of a firm and to resume it within a couple of days. After talking to IBES representatives, this happens when analysts are updating their beliefs about the firm and decide to suspend their previous rating a few days before issuing their new, updated rating.[6] [AC08] provide another explanation and claim that some analysts would discontinue their coverage only to resume it a few days later in an attempt to fool the market and start over with a 'clean' track record on the same stock. I am not interested in these signals which I don't expect to carry any relevant piece of information. Hopefully, the six-month threshold should filter out most of them. I use the following algorithm to identify reinitiations: I gather the discontinuation dates from the Stopped Recommendation File in IBES. This file also gives the name of the broker and the day coverage was dropped. The next recommendation published by the same broker on the same firm at least six months later is the reinitiation of coverage. I also want to know if the reinitiation is submitted by the same analyst that discontinued the coverage, or if the broker assigned a new analyst. However, the Stopped Recommendation file contains neither a final rating, nor the name of the analyst. Thus, for each observation in the Stopped Recommendation file, I identify the most recent recommendation that had been issued by the same broker on the same firm

[5] http://www1.nyse.com/pdfs/rule472.pdf

[6] This explanation would account for the presence of the peak of reinitiations I observe within 10 days after a discontinuation.

in the previous six months, and I record the analyst name and the corresponding rating. I consider this analyst to be the one that used to follow the firm, and the last known rating before the discontinuation can be compared to the rating on the reinitiation day to see if the reinitiation is also an upgrade (e.g the analyst increased his rating from Hold to Buy) or a downgrade.

Before starting the event-study, I take a few additional precautions. Because I want to evaluate and compare the informativeness of different types of recommendations, I need to ensure that recommendations do not fall on the same day as firm news. Previous work by [MS07] have shown that about 12% of recommendations fall in a three-day window around quarterly earnings announcements. Failing to remove these recommendations would wrongly attribute the price movement to the recommendation and not to the simultaneous corporate announcement. I obtain quarterly earnings announcement dates from Compustat and exclude recommendations that fall in a three-day window centered on the announcement day. I also prevent results from being biased by low priced stocks or market microstructure effects by removing stocks whose price is less than one dollar on the day before the announcement is announced. Finally, I keep stocks whose industry can be identified by its SIC number, and whose market value and book-to-market can be computed using Compustat and CRSP.

After applying these filters, I end up with 5,383 reinitiations of coverage with a positive rating (Buy or Strong Buy). Among those, 1,060 come from the same analyst that discontinued the coverage, [7] and 4,323 from a different analyst working at the same broker. Not surprisingly, there are far fewer reinitiations issued with a negative rating (827 cases), 215 coming from the same analyst that discontinued coverage. I can also identify 3,301 reinitiation-upgrades, 753 of which come from the same analyst, and 3,495 reinitiation downgrades, 1,016 coming from the same analyst. Reinitiations come from 3,020 different analysts who work for 281 different brokers and cover 3,085 different firms. From Table 1.1,

[7] Eliminating recommendations that fall in the three-day window centered on the firm quarterly announcements led to the loss of 184 reinitations by the same analyst with a positive rating and 172 upgrades by the same analyst.

the average firm subject to a reinitiation has an average market cap of 12 billion dollars and is followed by 15 analysts. Sixty percent of the recommendations are resumed after an interruption of 542 calendar days.

In the paper, I compare reinitiations to several benchmarks:

1. initiations of coverage: the first recommendation issued by an analyst on a firm. I go back to 1996 to make sure that the analyst didn't cover the firm in the past.

2. recommendation changes. Prior research has shown that recommendation changes are usually more informative than levels (see [Wom96] for example). A recommendation change is defined as the current rating minus the previous rating by the same analyst. IBES codes ratings from 1 (Strong Buy) to 5 (Strong Sell). An upgrade corresponds to a negative change in rating while a downgrade corresponds to a positive change in rating. A rating is considered to be outstanding if it has not been stopped by the broker. I exclude anonymous analyst codes.

Table 1.1: Characteristics of the recommendations

For each type of recommendation, the table lists the number of observations, the number of unique firms, the average market capitalization (in million dollars) and the average number of analysts who submitted forecasts in IBES in the six months before each recommendation announcement day.

Recommendation	N	Market Cap	Analysts
Positive Recommendations			
All Reinitiations	5,383	15,111	17.02
Same Analyst	*1,060*	*12,791*	*14.96*
Different Analyst	*4,323*	*15,666*	*17.53*
Initiations	3,472	8,986	13.66
Upgrades			
All Reintiations	3,301	11,643	17.01
Same Analyst	*753*	*10,072*	*15.22*
Different Analyst	*2,548*	*12,107*	*17.53*
Regular Upgrades	48,869	9,099	15.23
Negative Recommendations			
All Reinitiations	827	10,223	17.28
Same Analyst	*215*	*6,277*	*15.08*
Different Analyst	*612*	*11,572*	*18.05*
Initiations	606	7,193	14.72
Downgrades			
All Reintiations	3,495	12,789	17.67
Same Analyst	*1,016*	*9,756*	*16.49*
Different Analyst	*2,479*	*14,016*	*18.16*
Regular Downgrades	52,698	8,348	14.74

1.3 Short-term event study and univariate tests

I first perform univariate tests and compute the average cumulative abnormal returns (CAR) for each category of recommendation with the following convention: day 0 is the announcement day of the recommendation. If the recommendation is announced on a week-end or a holiday, day 0 is the next available trading day.

I use a two-day window to compute the daily return following the issuance of the recommendation. [8] Two-day CAR are defined as:

$$CAR_i = \prod_{t=0}^{1}(1 + R_{i,t}) - \prod_{t=0}^{1}(1 + R_{i,t}^{DGTW}) \tag{1.1}$$

where $R_{i,t}$ is the return of stock i on day t and $R_{i,t}^{DGTW}$ is the return on a benchmark portfolio with similar size, book to market (B/M) and momentum characteristics as the stock as advocated in [DGT97] (henceforth DGTW).

The benchmark portfolios are computed as follows: every July, firms are sorted into quintiles based on their size. The size breakpoints are obtained from NYSE firms only. Then, within each size quintile, firms are sorted into quintiles based on their industry-adjusted B/M ratios (based on their most recently available B/M data). Industry-adjusted B/M characteristics are calculated as in [CP98] and [Wer03]:

$$\frac{ln(B/M_{i,t}^{j}) - ln(B/M_{t}^{j})}{\sigma_j[ln(B/M_{i,t}^{j}) - ln(B/M_{t}^{j})]} \tag{1.2}$$

where $B/M_{i,t}^{j}$ is the book-to-market ratio of firm i, which belongs to industry j on the 30th of June of year t and $ln(B/M_{t}^{j})$ is the log book-to-market ratio of industry j (defined as the aggregate book value of all firms of that industry divided by their aggregate market value). The denominator is the standard deviation of the adjusted book-to-market ratio

[8] I find similar results with a three-day window centered on the announcement day

within industry j. I use the 48 industries defined on Ken French's website. [9]

Finally, every month, firms within each size-BM group are further sorted into quintiles based on the 12-month past stock returns skipping the most recent month. This procedure is similar to the one used in [LS11], except for the definition of the B/M ratio which follows [DGT97] and [Wer03].[10] Finally, within each characteristic portfolio, firms are equally weighted at the beginning of each month and the daily buy and hold returns are computed.

Table 1.2 reports the two-day CAR for each category of recommendations and tests whether the average CAR are significantly different between reinitiations and other types of recommendations. Standard errors are clustered by calendar day. For positive ratings, reinitiations of coverage by the same analyst produce abnormal returns of 1.70% (t=11.79), which are greater than the 1.07% (t=20.52) coming from reinitiations by a different analyst, and the difference is significant (t=4.02). Initiations of coverage produce CAR of 0.83% that are also dominated by reinitiations by the same analyst (the t-statistic of the difference is 4.84).

Besides, in line with the previous literature, recommendation changes lead to greater immediate market response than levels. Reinitiation upgrades from the same analyst lead to CAR of 2.31% (t=13.02), whereas upgrades by a different analyst are followed by CAR of 0.98% (t=14), and the difference is highly significant (t=6.86). The market treats reinitiation upgrades by the same analyst just as regular upgrades (CAR=2.51%): the 20 basis point difference in CAR is not significantly different from 0 (t=1.06). Similar conclusions hold for negative recommendations and downgrades. Reinitiations of coverage seem to convey valuable information to the market.

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[10] An alternative definition of the Book-to-Market ratio as in [FF06] yields similar results

Table 1.2: Two-day cumulative abnormal returns for all recommendation categories

The table shows the compounded stock returns between day 0 and day 1, the mean two-day cumulative abnormal returns between day 0 and day 1, and the number of recommendations that fall in each category. Cumulative abnormal returns are defined as the difference between the two-day compounded stock return and the two-day compounded return of a DGTW characteristic-matched portfolio. The table also reports the difference in the mean CAR between recommendation types. The sample is from 2003 to the end of June 2013. Recommendations that fall in a three-day interval centered on an earnings announcement day as reported by Compustat are excluded from the sample, as well as stocks with a lagged-price below \$1. The reported t statistics are based on standard errors clustered by calendar day. * significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

Recommendation	Actual Return (%)	Mean CAR (%)	t	N
Positive Recommendations				
1. All Reinitiations	1.34	1.20***	23.55	5,383
2. *Same Analyst*	*1.79*	*1.70****	*11.79*	*1,060*
3. *Different Analyst*	*1.23*	*1.07****	*20.52*	*4,323*
4. Initiations	0.54	0.83***	11.39	3,472
(2)-(3)	0.56	0.62***	4.02	
(2)-(4)	1.25	0.87***	4.84	
Upgrades				
5. All Reintiations	1.43	1.28***	18.82	3,301
6. *Same Analyst*	*2.33*	*2.31****	*13.02*	*753*
7. *Different Analyst*	*1.16*	*0.98****	*14.00*	*2,548*
8. Regular Upgrades	2.69	2.51***	79.39	48,869
(6)-(7)	1.17	1.33***	6.86	
(6)-(8)	–0.36	–0.20	–1.06	

Table 1.2 – *Continued from previous page*

Recommendation	Actual Return (%)	Mean CAR (%)	t	N
Negative Recommendations				
9. All Reinitiations	–1.38	–1.64***	–11.29	827
10. *Same Analyst*	*–1.47*	*–1.80****	*–4.49*	*215*
11. *Different Analyst*	*–1.35*	*–1.59****	*–11.55*	*612*
12. Initiations	–1.04	–0.78**	–2.45	606
(10)-(11)	–0.12	–0.21	–0.48	
(10)-(12)	–0.43	–1.02*	–1.89	
Downgrades				
13. All Reintiations	–1.15	–1.26***	–12.43	3,495
14. *Same Analyst*	*–2.27*	*–2.38****	*–8.16*	*1,016*
15. *Different Analyst*	*–0.69*	*–0.80****	*–10.44*	*2,479*
16. Regular Downgrades	–2.72	–2.74***	–69.48	52,698
(14)-(15)	–1.58	–1.57***	–5.06	
(14)-(16)	0.45	0.37	1.22	

1.4 Market underreaction

I now test whether reinitiations of coverage are associated with a drift at three-month and six-month horizons. Figure 1.1 shows the mean CAR of reinitiation upgrades and regular upgrades during the six months that follow the issuance of the recommendation. It clearly shows that the price adjustment of reinitiations is much slower than for upgrades, and extends during the whole period. On the other hand, for regular upgrades, the drift starts to revert shortly after the recommendation is issued (even though at a slow pace).

Figure 1.1: CAR for reinitiation upgrades and regular upgrades

The figure displays the mean CAR (in percentage) of reinitiation upgrades by the same analyst (plain line) and regular upgrades (dotted line). The horizontal axis gives the number of trading days with respect to the recommendation announcement date, from day -10 until day 120.

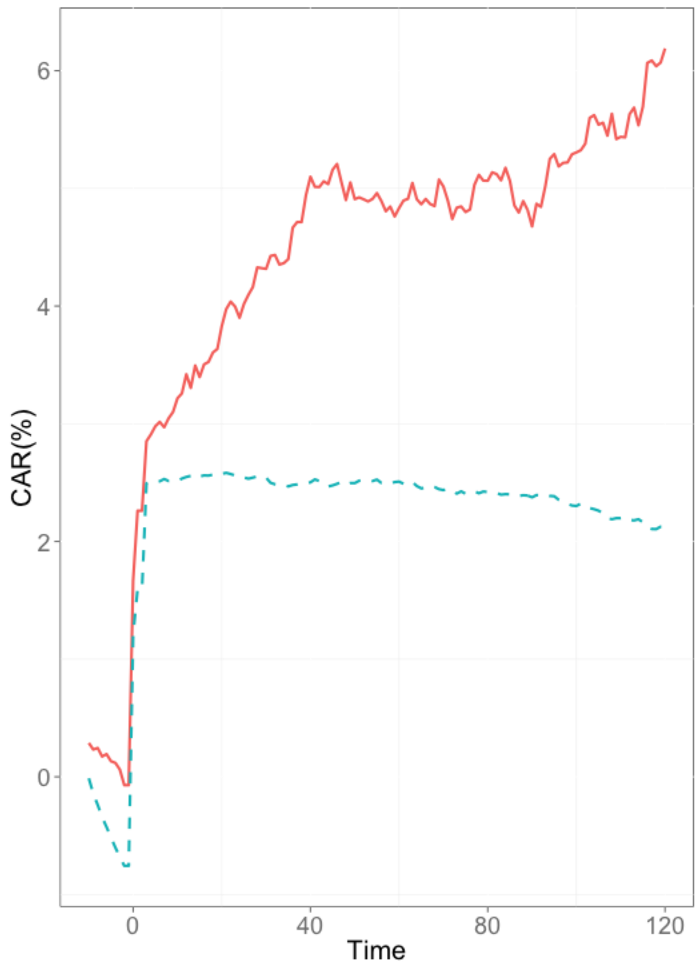

Table 1.3 shows the cumulative abnormal returns over a three-month period (between day 2 and day 63[11]). Positive reinitiations as a whole lead to a significantly positive drift (CAR=0.82%, t=3.28), but the CAR from reinitiations by the same analyst (CAR=2.18%, t=3.28) are greater than the CAR from reinitiations by a different analyst (CAR=0.49%, t=1.67). The difference is statistically significant (t= 2.22).

Just as before, reinitiations by a different analyst (CAR=0.49%) look very similar to initiations (CAR=0.46%). Besides, market underreaction is strongest for reinitiation upgrades, with a drift of 2.62% (t=3.24). On the contrary, regular upgrades do not lead to a drift at the three-month horizon (CAR=0.01%, t=0.07), and the CARs of reinitiation upgrades by the same analyst are significantly stronger than the CARs of regular upgrades (t=3.22). This is in line with previous literature: for example, [Wom96] and [Loh08] documented the existence of a significant but short-lived (one-month) post-recommendation drift for upgrades. My results confirm that the short-term valuation effect of regular upgrades is transitory and prices adjust very quickly. For negative ratings, it is more difficult to draw solid conclusions because of the small size of the sample (I only only have 211 reinitiations by the same analyst with a negative rating for example). Reinitiation downgrades by the same analyst produce an average negative CAR of -0.84% (t=-1.43). The only statistically significant drift comes from regular downgrades (CAR=-1.08%, t=-9.21). A longer persistence of the drift from regular downgrades had already been documented by [Wom96]. The author justified it by the greater reputation cost for an analyst to issue a negative recommendations or downgrades, which is likely to translate into "greater returns" for the analyst. The phenomenon can also be explained by short-sell constraints. The effect persists at the six-month horizon as shown in Table 1.4. The average CAR for reinitiations by the same analyst reaches 2.68% (t=2.70) and 3.31% for upgrades by the same analyst (t=2.74).

[11] These are trading days, using the 21 trading-day-per-month convention

Table 1.3: Three-month cumulative abnormal returns for all recommendation categories

The table shows the compounded stock returns between day 2 and day 63, the mean two-day cumulative abnormal returns between day 0 and day 1, and the number of recommendations that fall in each category. Cumulative abnormal returns are defined as the difference between the two-day compounded stock return and the two-day compounded return of a DGTW characteristic-matched portfolio. The table also reports the difference in the mean CAR between recommendation types. The sample is from 2003 to the end of June 2013. Recommendations that fall in a three-day interval centered on an earnings announcement day as reported by Compustat are excluded from the sample, as well as stocks with a lagged-price below \$1. The reported t statistics are based on standard errors clustered by calendar day. * significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

Recommendation	Actual Return (%)	Mean CAR (%)	t	N
Positive Recommendations				
1. All Reinitiations	4.41	0.82^{***}	3.03	5,373
2. *Same Analyst*	*6.53*	2.18^{***}	*3.28*	*1,056*
3. *Different Analyst*	*3.89*	0.49^{*}	*1.67*	*4,317*
4. Initiations	1.82	0.46	1.03	3,470
(2)-(3)	2.64	1.68^{**}	2.33	
(2)-(4)	4.71	1.71^{**}	2.20	
Upgrades				
5. All Reintiation Upgrades	4.77	1.07^{***}	3.03	3,296
6. *Same Analyst*	*7.17*	2.62^{***}	*3.24*	*750*
7. *Different analyst*	*4.06*	*0.62*	*1.58*	*2,546*
8. Regular Upgrades	3.36	0.01	0.07	48,786
(6)-(7)	3.11	1.99^{**}	2.22	
(6)-(8)	3.81	2.61^{***}	3.22	

Table 1.3 – *Continued from previous page*

Recommendation	Actual Return	Mean CAR	t	N
Negative Recommendations				
9. All Reinitiations	2.54	–0.77	–0.98	822
10. *Same Analyst*	*4.27*	*0.75*	*0.50*	*211*
11. *Different Analyst*	*1.94*	*–1.29*	*–1.40*	*611*
12. Initiations	1.46	–1.25	–1.28	602
(10)-(11)	2.33	2.05	1.15	
(10)-(12)	2.81	2.00	1.12	
Downgrades				
13. All Reintiations	2.95	$–0.67^{*}$	–2.03	3,475
14. *Same Analyst*	*3.46*	*–0.84*	*–1.43*	*1,002*
15. *Different Analyst*	*2.74*	*–0.60*	*–1.51*	*2,473*
16. Regular Downgrades	1.99	$–1.08^{***}$	–9.21	52,175
(14)-(15)	0.72	-0.24	-0.34	
(14)-(16)	1.47	0.24	0.40	

Table 1.4: Six-month cumulative abnormal returns for all recommendation categories

The table shows the compounded stock returns between day 2 and day 126, the mean cumulative abnormal returns between day 2 and day 63, and the number of recommendations that fall in each category. Cumulative abnormal returns are defined as the difference between the compounded stock return and the compounded return of a DGTW characteristic-matched portfolio. The table also reports the difference in the mean CAR between recommendation types. The sample is from 2003 to June 2013. Recommendations that fall in a three-day interval centered on an earnings announcement day (obtained from Compustat) are excluded from the sample, as well as stocks with a lagged price below $1. The reported t statistics are based on standard errors clustered by calendar day. * significant at $p < .10$; ** $p < .05$; *** $p < .01$

Recommendation	Actual Return (%)	Mean CAR (%)	t	N
Positive Recommendations				
1. All Reinitiations	8.32	1.23***	3.07	5,344
2. *Same Analyst*	*11.43*	*2.68***	*2.70*	*1,047*
3. *Different Analyst*	*7.56*	*0.88**	*2.02*	*4,297*
4. Initiations	4.32	0.18	0.33	3,451
(2)-(3)	3.87	1.80	1.59	
(2)-(4)	7.11	2.50**	2.02	
Upgrades				
5. All Reintiation Upgrades	8.82	1.91***	3.53	3,277
6. *Same Analyst*	*12.02*	*3.31****	*2.74*	*744*
7. *Different Analyst*	*7.88*	*1.49***	*2.48*	*2,533*
8. Regular Upgrades	6.58	–0.59***	-4.08	48,298
(6)-(7)	4.14	1.82	1.33	
(6)-(8)	5.44	3.90***	3.19	

Table 1.4 – *Continued from previous page*

Recommendation	Actual Return	Mean CAR	t	N
Negative Recommendations				
9. All Reinitiations	5.91	–2.14*	–2.05	818
10. *Same Analyst*	*7.17*	*–0.83*	*–0.48*	*211*
11. *Different Analyst*	*5.48*	*–2.60**	*–2.05*	*607*
12. Initiations	5.26	–1.45	–0.96	594
(10)-(11)	1.69	1.77	0.78	
(10)-(12)	1.91	0.62	0.26	
Downgrades				
13. All Reintiations	5.98	–1.87***	–4.15	3,425
14. *Same Analyst*	*6.64*	*–1.91***	*–2.32*	*971*
15. *Different analyst*	*5.72*	*–1.85****	*–3.44*	*2,454*
16. Regular Downgrades	5.14	–1.96***	–13.58	50,714
(14)-(15)	0.92	–0.06	–0.06	
(14)-(16)	1.50	0.05	0.06	

1.5 Portfolio strategies

Another classical way to estimate the economic relevance of market inefficiencies is to measure the abnormal return of a portfolio trading strategy. I form calendar time portfolios and compare the abnormal returns from investing in stocks that are reinitiated versus other types of recommendations over fixed horizons (three months and six months). A stock enters a portfolio at the close of trading on the day the recommendation is announced. If the recommendation is announced after market close (after 4pm), the stock enters the portfolio at the close of the following trading day. If more than one broker takes the same action on a particular stock, the stock appears multiple times in the portfolio, once for each broker. Portfolios are updated every day and firms leave a portfolio at the end of the investment horizon or at the closing of the day its recommendation is changed or coverage discontinued. Equally weighting daily returns and thus assuming daily rebalancing would overstate returns because of the bid-ask bounce as explained in [LBT99]. Therefore, daily returns are computed in a buy-and-hold manner that assumes an equal initial investment in each recommendation, as in [BLT07]. The return of a portfolio on day t is:

$$R_{p,t} = \frac{\sum_{i=1}^{n_t} x_{i,t} R_{i,t}}{\sum_{i=1}^{n_t} x_{i,t}} \tag{1.3}$$

where $R_{i,t}$ is the gross return on stock i in date t, n_t is the number of stocks in the portfolio and $x_{i,t}$ is the compounded daily return of stock i from the day it entered the portfolio (the close of the trading day the recommendation was announced) through day (t-1) and is equal to 1 for a stock that received a recommendation on day (t-1). Daily portfolio returns are compounded in monthly returns, which are used in the [Cah97] four-factor model. [12] The intercept α_j obtained from the estimation of the monthly time-series regressions for each portfolio j gives the average monthly abnormal return of that strategy:

$$R_t^j - R_{ft} = \alpha_j + \beta_j (R_{mt} - R_{ft}) + \gamma_j SMB_t + \theta_j HML_t + \rho_j UMD_t + \epsilon_{jt} \tag{1.4}$$

where R_t^j is the month t return on portfolio j, R_{ft} is the month t risk-free rate, $R_{m,t}$ is the month t return on the market index and SMB_t is the month t return on a value-weighted portfolio of small-cap stocks minus the return on a value-portfolio of large stocks, HML_t is the month t return on a value-weighted portfolio of high book-to-market stocks minus the return on a value-weighted return of stocks with low book-to-market return, UMD_t is the month t return on a value-weighted portfolio of stocks with high recent returns minus the month t return on a value-weighted return of stocks with low recent returns [13] and ϵ_{jt} is the error term in the regression.

I include an estimate of transaction costs since previous studies, like [BLM01], have cast

[12] Regressions based on daily returns yielded similar results.
[13] Monthly values of the 4 factors are from Ken French's website.

doubt as to whether positive abnormal returns could be earned on analyst recommendations once transaction costs are accommodated. [Bhu94] or [CGS07] have even claimed that transaction costs prevent informed investors from correcting the post-earnings announcement drift. I implement the algorithm provided by [CS12] which can be used to produce daily spread estimates. [14] Their method relies on two ideas: first of all, the daily high (resp. low) prices are very likely to be buyer (resp. seller) initiated, which implies that the high-to-low ratio incorporates both the underlying volatility of the stock and the bid-ask spread. The second idea is that the fundamental volatility component of the high-to-low ratio increases linearly with time, while the bid-ask spread is assumed to stay constant over a short time window. They show that the spread S can be estimated as:

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{1.5}$$

I use their closed-form solution for α (see Appendix for details). For each recommendation in my data, I estimate the spread using any two consecutive trading days on the month the recommendation is issued, and I use the average value as my estimate of the spread.

Firms enter the portfolio at the closing of the day that follows the recommendation issuance, and leave at the end of the investment horizon. First-day and last-day returns are reduced by half the spread estimate each time.[15] Daily returns are computed using portfolio weights that reflect the cumulative value of the initial investment of $1 in each stock when it entered the portfolio. Thus, there is no rebalancing (except when a stock leaves the portfolio after a recommendation change before the end of the investment horizon), which reduces transaction costs. Table 1.5 shows that a trading strategy that invests in stocks reinitiated by the same analyst achieves an average monthly abnormal return of 0.55% (t=2.2), which is significantly greater than the monthly abnormal return achieved from initiations of coverage. Investing in reinitiation upgrades leads to an average monthly abnormal return of 0.64% (t=2.1), which is greater than the monthly return from regular upgrades.

[14] I neglect other components of transaction costs like commissions or price impact.

[15] The full spread is my proxy for the cost of a round-trip transaction.

Table 1.5: Three-month calendar time portfolios after transaction costs-Positive ratings and upgrades

Stocks enter a portfolio at the market close on the day the recommendation is announced and remain in the portfolio for 3 months. Portfolios are updated every day and value-weighted daily returns are computed according to equation (3). Daily returns are then compounded in monthly returns. First-day and last-day returns are reduced by half the spread, according to the procedure outlined in [CS12]. The table reports the regression estimates from regressing the monthly returns in excess of the risk-free rate on the [Cah97] four-factor model. The intercept gives the average monthly buy-and-hold abnormal returns. Standard errors are computed with the [NW94] adjustment. In addition, the following rule is used for significance: * significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

	All Reinitiations	Same Analyst	Different Analyst	Initiations
Intercept	0.32^{*}	0.55^{**}	0.17	-0.09
	(0.16)	(0.25)	(0.19)	(0.21)
RMRF	1.13^{***}	1.25^{***}	1.10^{***}	1.27^{***}
	(0.05)	(0.08)	(0.06)	(0.06)
SMB	0.49^{***}	0.42^{***}	0.51^{***}	0.32^{***}
	(0.09)	(0.13)	(0.11)	(0.10)
HML	-0.18	-0.19	-0.18	-0.09
	(0.13)	(0.16)	(0.14)	(0.11)
UMD	-0.07	-0.20^{*}	-0.03	-0.02
	(0.07)	(0.10)	(0.06)	(0.05)
N	121	121	121	121
adj. R^2	0.91	0.84	0.87	0.87

Table 1.5 – *Continued from previous page*

	All Reinitiations Upgrades	Same Analyst Upgrades	Different Analyst Upgrades	Regular Upgrades
Intercept	0.25*	0.64**	0.19	-0.04
	(0.15)	(0.30)	(0.24)	(0.08)
RMRF	1.16***	1.16***	1.14***	1.13***
	(0.05)	(0.11)	(0.06)	(0.03)
SMB	0.52***	0.80***	0.61***	0.57***
	(0.10)	(0.14)	(0.13)	(0.05)
HML	-0.05	-0.19	-0.11	0.05
	(0.12)	(0.14)	(0.16)	(0.05)
UMD	-0.10**	-0.40***	-0.04	-0.10**
	(0.04)	(0.10)	(0.05)	(0.04)
N	121	121	121	121
adj. R^2	0.92	0.84	0.83	0.97

Table 1.6: Comparing portfolios' abnormal returns

I compare the abnormal returns from two types of recommendations by forming a hedge portfolio that is long one type of recommendation and short the other one. The daily returns from that strategy are compounded into monthly returns that are regressed on the [Cah97] four factors. The table reports the intercept and the corresponding t statistics with the [NW94] standard errors.

	Intercept	t
Positive ratings		
Same Analyst versus Different Analyst-Positive ratings	0.38	1.40
Same Analyst versus Initiation	0.64^{**}	2.48
Upgrades		
Same Analyst versus Different Analyst upgrade	0.45	1.36
Same Analyst versus Upgrades	0.68^{**}	2.48

With a six-month investment horizon, abnormal returns remain significantly positive both for positive reinitiations by the same analyst and reinitiation upgrades by the same analyst, as reflected in Table 1.7, and reinitiations are the only type of recommendation that leads to a profitable strategy.

Table 1.7: Six-month calendar time portfolios after transaction costs-Positive ratings and upgrades

Stocks enter a portfolio at the market close on the day the recommendation is announced and remain in the portfolio for 6 months. Portfolios are updated every day and value-weighted daily returns are computed according to equation (3). Daily returns are then compounded in monthly returns. First-day and last-day returns are reduced by half the spread, according to the procedure outlined in [CS12]. The table reports the regression estimates from regressing the monthly returns in excess of the risk-free rate on the [Cah97] four-factor model. The intercept gives the average monthly buy-and-hold abnormal returns. Standard errors are computed with the [NW94] adjustment. In addition, the folowing rule is used for significance: * significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

	All Reinitiations	Same Analyst	Different Analyst	Initiations
Intercept	0.30^{**}	0.43^{***}	0.23	-0.07
	(0.14)	(0.16)	(0.14)	(0.18)
RMRF	1.12^{***}	1.16^{***}	1.12^{***}	1.25^{***}
	(0.04)	(0.07)	(0.04)	(0.06)
SMB	0.47^{***}	0.41^{***}	0.50^{***}	0.41^{***}
	(0.07)	(0.10)	(0.08)	(0.09)
HML	-0.19	-0.11	-0.23^{**}	-0.18^{*}
	(0.13)	(0.12)	(0.12)	(0.10)
UMD	-0.03	-0.14	-0.00	-0.03
	(0.04)	(0.09)	(0.03)	(0.06)
N	121	121	121	121
adj. R^2	0.93	0.88	0.92	0.89

Table 1.7 – *Continued from previous page*

	All Reinitiations Upgrades	Same Analyst Upgrades	Different Analyst Upgrades	Regular Upgrades
Intercept	0.21*	0.61***	0.33	-0.02
	(0.12)	(0.17)	(0.21)	(0.09)
RMRF	1.15***	1.13***	1.15***	1.14***
	(0.04)	(0.08)	(0.05)	(0.04)
SMB	0.48***	0.50***	0.58***	0.53***
	(0.07)	(0.14)	(0.09)	(0.05)
HML	-0.08	-0.04	-0.23	0.05
	(0.10)	(0.10)	(0.15)	(0.06)
UMD	-0.07**	-0.26**	-0.08*	-0.07*
	(0.03)	(0.11)	(0.04)	(0.04)

Table 1.8: Comparing portfolios' abnormal returns

I compare the abnormal returns from two types of recommendations by forming a hedge portfolio that is long one type of recommendation and short the other one. The daily returns from that strategy are compounded into monthly returns that are regressed on the [Cah97] four factors. The table reports the intercept and the corresponding t statistics with [NW94] standard errors.

	Intercept	t
Positive ratings		
Same Analyst versus Different Analyst-Positive ratings	0.21	1.11
Same Analyst versus Initiation	0.51**	2.57
Upgrades		
Same Analyst versus Different Analyst upgrade	0.27	1.03
Same Analyst versus Upgrades	0.63***	3.29

1.6 Possible explanations

The previous section documented the existence of an incomplete initial market reaction associated with reinitiations of coverage by the same analyst and reinitiation upgrades. In this section, I investigate different candidate explanations.

1.6.1 Limited attention

Attention is either endogenous or exogenous: it can be the result of a voluntary strategy of an agent who chooses to focus on a given object [16] or the reaction to a stimulus. [HT03] have shown that if investors have limited attention and information-processing power, the framing of accounting disclosures will have an impact on investors' perceptions: information which is easy to absorb or presented in a salient form will be incorporated more easily than information which is less salient or implicit. Other works by [PJ98] found a significant decline in subjects' performance when asked to accomplish several tasks at the same time, in particular when those tasks are similar.

In this paper, I consider reinitiations as a stimulus and test whether some comparative statics can partially account for the slow price adjustment. As a preliminary remark, it is worth mentioning [HLT09]'s distraction hypothesis which explains why earnings announcements that are released on the same day as numerous competing announcements from other firms lead to a strong market underreaction. In a similar vein, I note the presence of lots of irrelevant stimuli in my data. I can identify about 30,000 cases for which a given analyst stops the coverage of a firm and resumes it within six months (in most cases within a few days). They represent more than three times the total number of reinitiations in my sample and their existence can be explained by various reasons. For example, analysts might place their rating under review. They can also be justified by regulation (when the stock is placed on a restricted list because the broker is involved in some underwriting transaction with the

[16] For example, in the model of [PX06] investors' limited attention leads them to devote more time to analyze market and sector information than firm-specific information.

firm). For any of the previous explanations, one would not expect much valuable information to be conveyed in the announcement of these signals, but they would rather play the role of a smoke screen that absorbs some of the limited attention capacity of market participants and prevents them from fully responding to the information content of the truly informative reinitiations.

Several proxies for investor attention have been proposed in the recent literature: analyst coverage ([Loh08]), firm announcements on Fridays ([DP09]), and turnover ([Loh08]). Among these variables, turnover is likely to be the variable with the highest correlation with attention ([HPX09]). It shouldn't come as a surprise: after all, turnover can be seen as a by-product of investors' preferences and attention because if investors don't pay attention to a stock, they won't trade it. [GKM01] show that trading volume (the other name under which turnover is often referred to in the literature) can predict future price changes: an increase in volume increases a stock's visibility and attention. [BO08] use changes in trading volume as a proxy for changes in investors' attention. For each trading day, daily turnover is the number of shares traded divided by the total number of shares outstanding. [17] I compute the average daily turnover for each stock during the three months that precede the discontinuation of coverage and allocate each observation to one of five portfolios. I estimate the average daily turnover during the three months that follow each reinitiation. It appears that stocks that had a lower initial turnover experience a significant increase in their turnover in the post-reinitiation period.

For example, the turnover of reinitiations by the same analyst in portfolio 1 increases by seven basis points (t=6.21). Portfolios 1 to 3 experience a significant increase in their turnover, and as the level of prior turnover increases, the magnitude of the change decreases. Turnover even decreases for the group of stocks with the highest level of prior turnover, and the spread between the extreme portfolios is highly significant.

[17] As explained in [LM97], for NASDAQ firms, one needs to divide the daily volume by two to avoid double counting inter-dealer trades.

Table 1.9: Change in turnover after reinitiations of coverage

For each firm subject to a reinitiation of coverage, the average daily turnover is estimated during the three months that end on the day the recommendation was discontinued (in the window [-63, -2]). Reinitiations are then sorted into five groups based on their estimated turnover. In Panel A, the average daily turnover is estimated in the three months that follow the reinitiation announcement date (in the window [2,63]), and the table reports the average difference in turnover between the post-recommendation period and the pre-discontinuation period for each portfolio. Panel B reports the average change in daily turnover between the six-month post-recommendation window (between days [2,120]) and the pre-discontinuation period. Standard errors are clustered by calendar day.* significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

Panel A: Three-month period after the reinitiation announcement

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	0.05^{***}	0.07^{***}	0.04^{***}	0.06^{***}	0.07^{***}	0.05^{***}
	(11.22)	(6.21)	(9.42)	(9.12)	(5.74)	(7.19)
2	0.06^{***}	0.07^{***}	0.06^{***}	0.06^{***}	0.08^{***}	0.06^{***}
	(8.58)	(5.27)	(7.17)	(6.86)	(5.19)	(5.27)
3	0.04^{***}	0.04^{**}	0.04^{***}	0.06^{***}	0.04^{**}	0.07^{***}
	(4.84)	(2.16)	(4.40)	(5.45)	(1.99)	(5.13)
4	0.01	0.02	0.01	0.02	0.03	0.01
	(1.09)	(0.52)	(0.97)	(1.19)	(0.68)	(0.97)
5	-0.17^{***}	-0.20^{**}	-0.16^{***}	-0.19^{***}	-0.36^{***}	-0.15^{***}
	(-4.76)	(-2.48)	(-4.08)	(-4.30)	(-3.11)	(-3.15)
P5-P1	-0.22^{***}	-0.27^{***}	-0.20^{***}	-0.25^{***}	-0.44^{***}	-0.20^{***}
	(6.15)	(3.29)	(5.17)	(5.54)	(3.73)	(4.15)

Table 1.9 – *Continued from previous page*

Panel B: Six-month period after the reinitiation announcement

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	0.06***	0.07***	0.05***	0.06***	0.08***	0.06***
	(12.77)	(7.25)	(10.64)	(9.42)	(5.79)	(7.53)
2	0.07***	0.08***	0.07***	0.07***	0.10***	0.07***
	(11.00)	(5.58)	(9.58)	(9.93)	(5.67)	(8.04)
3	0.05***	0.03	0.06***	0.06***	0.03	0.07***
	(4.95)	(1.42)	(4.77)	(6.34)	(1.57)	(6.34)
4	0.02	0.01	0.02	0.03*	0.01	0.03**
	(1.47)	(0.24)	(1.56)	(1.86)	(0.30)	(2.03)
5	-0.20***	-0.28***	-0.18***	-0.24***	-0.42***	-0.19***
	(-5.96)	(-3.47)	(-4.91)	(-5.53)	(-3.55)	(-4.33)
P5-P1	-0.26***	-0.36***	-0.23***	-0.30***	-0.50***	-0.24***
	(7.65)	(4.36)	(6.30)	(6.94)	(4.19)	(5.53)

These results suggest that reinitiations tend to be followed by an increased interest of investors, and the differential change in turnover across portfolios is consistent with an underreaction story. [18]

Then I check whether a lower initial level of attention is associated with a stronger drift. Like [HPX09], I measure the average daily turnover of each stock in the year that precedes the reinitiation (stopping two days before the announcement date). I allocate each reinitiation to one of five portfolios sorted by the average turnover (I obtain the breakpoints using all the recommendations present in this study). Table 1.10 shows the CAR for each portfolio sorted on turnover: for positive reinitiations of coverage, stocks in the lowest two turnover quintiles exhibit the highest abnormal returns during the three months that follow the reinitiation (for portfolio 1: CAR=2.56%, t=2.81 and for portfolio 2: CAR=1.98% t=2.24). CAR decrease as we move from portfolio 1 to portfolio 5 (in portfolio 5: CAR=1%, t=0.73). For reinitiation upgrades by the same analyst, we observe a similar pattern, with the stronger CAR in the lowest turnover portfolios (CAR=3.86%, t=3.54) , and the difference between portfolio 5 and portfolio 1 (-3.18%) is statistically significant (t=1.72). Stocks that benefited from less attention before the reinitiation issuance display a stronger drift. For reinitiations by a different analyst, there is no monotonic pattern and no portfolio has significant CAR, which is consistent with the absence of a clear drift from Tables 1.3 or 1.4. At the six-month horizon, the results are mainly driven by the lowest quintile portfolio, which displays a strong drift (CAR=3.61%, t=2.52). [19]

[18] The average firm in the highest quintile is of smaller size than in the other quintiles. The decrease in turnover for these stocks is consistent with a story where attentive investors trade quickly after the reinitiation is announced, leading to a peak of trading, which is followed by lower volumes in the following weeks.

[19] These results are unlikely to be mainly driven by a size effect. Indeed, [CS00] find that turnover and size are weakly correlated. I checked the mean market capitalization of the portfolios obtained from the sort on turnover and find that portfolios 2 and 3 contain bigger firms while portfolio 5 smaller firms.

Table 1.10: Average CAR of portfolios sorted by prior turnover-Positive ratings

All firms subject to one of the following recommendations (reinitiations, initiations, upgrades or downgrades) are sorted in five portfolios based on their average turnover in the year that precedes the recommendation date (ending two days before the announcement date). The portfolio breakpoints are based on all the recommendations types (reinitiations, initiations, upgrades, downgrades). For Nasdaq firms, CRSP's volume is divided by two to account for inter-dealer double counting. All renitiations are thus placed on one of the 5 portfolios, whose average CAR over three-month horizon or six-month horizon is reported. The last three columns are reinitiations coupled with upgrades. * significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

Panel A: Three-month period after the reinitiation announcement

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	1.01**	2.56***	0.40	0.71	3.86***	-1.00
	(2.13)	(2.81)	(0.73)	(1.10)	(3.54)	(-1.27)
2	0.70*	1.98**	0.36	1.34***	3.23***	0.67
	(1.74)	(2.24)	(0.80)	(2.63)	(3.06)	(1.12)
3	-0.82*	-0.45	-0.90*	-0.59	0.28	-0.83
	(-1.96)	(-0.46)	(-1.95)	(-1.18)	(0.25)	(-1.47)
4	-0.01	1.35	-0.36	0.25	-0.26	0.42
	(-0.03)	(1.42)	(-0.74)	(0.48)	(-0.23)	(0.72)
5	0.54	1.00	0.41	0.85	0.68	0.91
	(0.92)	(0.73)	(0.64)	(1.20)	(0.45)	(1.12)
P5-P1	-0.47	-1.57	0.01	0.15	-3.18*	1.91*
	(0.63)	(0.97)	(0.02)	(0.16)	(1.72)	(1.70)

Table 1.10 – *Continued from previous page*

Panel B: Six-month period after the reinitiation announcement

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	1.82***	3.61**	1.20	1.56*	4.75***	0.08
	(2.61)	(2.52)	(1.51)	(1.66)	(2.69)	(0.07)
2	0.47	0.79	0.39	1.35*	1.59	1.27
	(0.80)	(0.58)	(0.60)	(1.73)	(0.99)	(1.42)
3	-1.19*	-0.07	-1.41**	-0.11	1.76	-0.57
	(-1.89)	(-0.04)	(-2.06)	(-0.14)	(0.96)	(-0.67)
4	-0.31	0.05	-0.39	0.35	-2.08	0.98
	(-0.46)	(0.03)	(-0.53)	(0.42)	(-1.06)	(1.08)
5	1.23	2.98	0.81	1.00	1.83	0.78
	(1.30)	(1.27)	(0.78)	(0.87)	(0.73)	(0.60)
P5-P1	-0.59	-0.63	-0.39	-0.57	-2.91	0.70
	(0.51)	(0.23)	(0.31)	(0.38)	(0.95)	(0.41)

As a robustness check, I use another proxy for market attention: analyst coverage. Using the forecast file in IBES, for each stock I compute the total number of analysts who issued earnings forecasts in the year that precedes the reinitiation. I sort each stock in three portfolios (the breakpoints are determined using all the recommendations types). Table 1.11 shows that stocks that received a lower level of coverage in the pre-reinitiation period, exhibit significantly positive CAR (however the difference between portfolios 1 and 3 is not significantly different from 0 for reinitiations by the same analyst). For reinitiation upgrades, the CAR in portfolio 1 are significantly positive (CAR=5.54%, t=3.40), and the CAR in portfolios 2 and 3 are lower. Moreover, the difference between extreme portfolios is significantly different from 0 (-4.04% and a t-statistic of 2.01).

However, one might be concerned that analyst coverage is highly correlated with firm size, as shown in [Bus89]. [20] I follow [HLS00] and control for size by defining a residual analyst coverage measure. Each month, I regress the $log(1 + Analysts)$ on $log(Size)$ and take the residuals. I form three portfolios (the breakpoints being estimated using all the recommendations studied in this paper). The results from Table 1.12 are relatively similar to those from the previous table. At the three-month horizon, for positive reinitiations by the same analyst, portfolio 1 and 2 have significantly positive CAR (for portfolio 1: CAR=2.13%, t=2.29 and for portfolio 2: CAR=2.16%. t=1.67), in contrast to portfolio 3 (CAR=1.35%, t=1.10). But the difference between portfolio 1 and 3 is not significantly different from 0 (t=0.82). On the other hand, for upgrades by the same analyst, the CAR in portfolio 1 are significantly greater than 0 (CAR=5.54%, t=3.40), and significantly greater than the CAR from portfolio 3 (for portfolio 3: CAR=1.49, t=1.20, and the t-statistic of the difference in CAR between portfolio 1 and 3 is 2.01).

Thus, there is some evidence that for reinitiation upgrades by the same analyst, low coverage stocks respond more slowly than high coverage stocks, which means that those analysts are important to help the stock adjust to firm information.

The results using analyst coverage are weaker than the findings using turnover, but as mentioned above, analyst coverage has been shown to be an inferior proxy of attention in comparison to turnover. Overall, there is some evidence, even though not perfect, that a lower level of attention is followed by a stronger drift for reinitiations by the same analyst. Limited attention could thus partially explain the existence of the drift.

[20] As explained in [HLS00] size is not necessarily a clean measure of gradual information diffusion or attention. On the one hand, small firms are subject to less market marking or attention, which could favor market underreaction. On the other hand, for smaller stocks, a more limited investor participation implies that supply shocks are more likely to lead to reversals.

Table 1.11: Average CAR by analysts coverage groups-Positive ratings

Reinitiations are sorted in three portfolios depending on their analyst coverage. The average CARs are reported for each portfolio. Standard errors are clustered by calendar day. * significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

Panel A: Three-month period after the reinitiation announcement

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	1.71***	2.94**	1.31*	2.34**	5.54***	1.00
	(2.68)	(2.35)	(1.77)	(2.55)	(3.40)	(0.92)
2	0.65	2.53**	0.20	0.74	1.00	0.67
	(1.40)	(2.11)	(0.39)	(1.27)	(0.69)	(1.05)
3	0.35	1.19	0.19	0.63	1.49	0.42
	(0.98)	(1.16)	(0.49)	(1.30)	(1.20)	(0.80)
P3-P1	-1.21*	-1.31	-1.08	-1.59	-4.04**	-0.45
	(1.65)	(0.82)	(1.30)	(1.56)	(2.01)	(0.38)

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	1.47	2.98	0.98	3.48**	6.11**	2.39
	(1.40)	(1.46)	(0.80)	(2.16)	(2.47)	(1.19)
2	1.39**	3.64**	0.85	1.93**	2.23	1.84*
	(1.96)	(2.08)	(1.09)	(2.19)	(1.01)	(1.94)
3	1.15**	1.75	1.03*	1.48**	2.16	1.32*
	(2.11)	(1.10)	(1.77)	(2.10)	(1.19)	(1.69)
P3-P1	-0.32	-1.23	0.06	-2.00	-3.96	-1.07
	(0.27)	(0.48)	(0.04)	(1.15)	(1.29)	(0.50)

Table 1.12: Average CAR by residual analysts coverage groups-Positive ratings

Reinitiations are sorted in three portfolios depending on their residual analyst coverage. The average CARs are reported for each portfolio. Standard errors are clustered by calendar day. * significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

Panel A: Three-month period after the reinitiation announcement

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	1.72^{***}	2.13^{**}	1.56^{***}	1.95^{***}	4.27^{***}	0.95
	(3.43)	(2.29)	(2.67)	(2.91)	(3.67)	(1.18)
2	0.47	2.16^{*}	0.14	0.49	1.69	0.18
	(1.13)	(1.67)	(0.33)	(0.91)	(1.06)	(0.33)
3	0.32	1.35	0.11	0.83	0.99	0.78
	(0.70)	(1.10)	(0.23)	(1.36)	(0.70)	(1.14)
P3-P1	-1.39^{**}	-0.78	-1.45^{*}	-1.12	-3.27^{*}	-0.17
	(2.06)	(0.51)	(1.88)	(1.24)	(1.77)	(0.16)

Panel B: Six-month period after the reinitiation announcement

Quintile	All Positive Reinitiations	Same Analyst	Different Analyst	Reinitiation Upgrades	Same Analyst	Different Analyst
1	1.89^{**}	2.42	1.68^{*}	3.31^{***}	5.24^{**}	2.48^{**}
	(2.46)	(1.61)	(1.91)	(3.08)	(2.57)	(1.98)
2	1.17^{*}	4.08^{**}	0.59	1.08	2.94	0.60
	(1.86)	(2.11)	(0.90)	(1.37)	(1.32)	(0.73)
3	1.13	1.70	1.02	2.07^{**}	1.59	2.19^{*}
	(1.52)	(0.90)	(1.23)	(2.11)	(0.76)	(1.94)
P3-P1	-0.75	-0.72	-0.67	-1.24	-3.65	-0.28
	(0.71)	(0.30)	(0.56)	(0.86)	(1.24)	(0.17)

1.6.2 Operating performance changes

Analysts who reinitiate the coverage of a firm have a prior knowledge of the company and its management, and they have the option to choose whether they are willing to resume coverage, at what rating, and at what time. Thus I would expect those analysts to reinitiate the coverage of firms whose performance is about to improve. Are reinitiations coincidental with a cross-sectional improvement in the operating performance of firms? [21] I look at the change in return on assets (ROA) and the change in EBIT margin from the year that precedes the reinitiation to the year that follows it. Return on Asset (ROA) is defined as the ratio of operating income after depreciation (Compustat item OAIDP) over total assets (Compustat item AT). I substract the median industry ROA for each fiscal year (using the 48 industries defined on Kenneth French's website). In Table 1.13, I find that the ROA of reinitiations by the same analyst and reinitiation upgrades by the same analyst decreased in the year that precedes the reinitiation ($p > 0.1$), but increased both in the year of the reinitiation and the following year. The effect is stronger for reinitiation upgrades by the same analyst, with a 0.17% increase ($p < 0.10$) on the year of the reinitiation followed by another increase of the ROA in the following year (a 0.30% jump, $p < 0.05$). Interestingly, reinitiations by a different analyst display a different pattern: the increase in ROA starts in the year before the reinitiation ($p < 0.01$) and continue on the year of the reinitiation ($p < 0.10$) but flattens the year after the reinitiation ($p > 0.1$). Moreover, regular upgrades follow a different pattern because the ROA goes down for each of the 3 years considered: I find a 0.06% decline followed by another 0.03% and a 0.02% decline, which are all highly significant ($p < 0.01$ in each case), even though their economic magnitude is limited. [22]

[21] Even though, I believe reinitiations could be used to uncover the true expectations of analysts, there is still a possibility that their decision is partially biased by the desire to gain some underwriting business for their broker. But, such a bias would go against me finding significant improvements in the firms' operating performance.

[22] During each of the two years before the recommendations issuance, the levels of ROA were not statistically different between regular upgrades and upgrades by the same analyst, but as explained, they seem to part from the year of the reinitiation.

Table 1.13: Change in Return on Assets (ROA) around recommendation announcements

The table reports the change in Return on Assets (ROA) for firms that are subject to each type of recommendation. ROA is the ratio of operating income after depreciation (Compustat item OAIDP) over total assets (Compustat item AT). I subtract the median industry ROA for each fiscal year (using the 48 industries from Ken French's website). Year 0 is the fiscal year that ends at least 3 months after the issuance of the recommendation and $\Delta ROA(0)$ is the change in ROA between year 0 and the previous fiscal year. The table also reports the difference between two recommendation types and significance is found by testing the null hypothesis that the median values are equal across the two recommendation types. * significant at $p < .10$; $**p < .05$; $^{***}p < .01$

Recommendation	$\Delta ROA(-1)$	$\Delta ROA(0)$	$\Delta ROA(1)$
Positive Recommendations			
1. All Reinitiations	0.16***	0.13**	-0.06***
2. *Same Analyst*	*-0.04*	*0.15**	*0.22*
3. *Different Analyst*	*0.20****	*0.11*	*-0.11****
4. Initiations	0.13**	0.07	-0.11***
(2)-(3)	-0.24***	0.03	0.33***
(2)-(4)	-0.17**	0.08	0.33***
Upgrades			
5. All Reinitiations	0.12**	0.16**	0.07
6. *Same Analyst*	*-0.08*	*0.17**	*0.30***
7. *Different Analyst*	*0.17****	*0.14**	*0.02*
8. Regular Upgrades	-0.06***	-0.03***	-0.02***
(6)-(7)	-0.26**	0.03	0.27**
(6)-(8)	-0.02	0.20**	0.31***

Table 1.13 – *Continued from previous page*

Recommendation	$\Delta ROA(-1)$	$\Delta ROA(0)$	$\Delta ROA(1)$
Negative Recommendations			
9. All Reinitiations	-0.20*	-0.16**	0.06
10. *Same Analyst*	*-0.19*	*-0.34**	*-0.09*
11. *Different Analyst*	*-0.21*	*-0.13**	*0.13*
12. Initiations	-0.18***	-0.39***	-0.06
(10)-(11)	0.03	-0.21	-0.22
(10)-(12)	-0.01	0.06	-0.03
Downgrades			
13. All Reinitiations	-0.09***	-0.15***	0.00
14. *Same Analyst*	*-0.13***	*-0.30****	*-0.06*
15. *Different Analyst*	*-0.07***	*-0.10****	*0.02*
16. Regular Downgrades	-0.02***	-0.23***	-0.09***
(14)-(15)	-0.06	-0.20**	-0.08
(14)-(16)	-0.11	-0.07	0.03

Comparing the different recommendation types, reinitiation upgrades by the same analyst experience a significantly greater increase in profitability than regular upgrades both on the year the recommendation is announced and the subsequent year. Table 1.14 compares the changes in industry-adjusted EBIT margins (defined as EBIT on sales) and reaches very similar conclusions.

Table 1.14: Change in EBIT margin around recommendation announcements

The table reports the change in EBIT margin for firms that are subject to each type of recommendation, where EBIT is the ratio of EBIT over sales. I substract the median industry EBIT margin for each fiscal year (using the 48 industries from Ken French's website). Year 0 is the fiscal year that ends at least 3 months after the issuance of the recommendation and $\Delta EBIT(0)$ is the change in EBIT margin between year 0 and the previous fiscal year. The table also reports the difference between two recommendation types and significance is found by testing the null hypothesis that the median values are equal across the two recommendation types. * significant at $p < .10$; $^* * p < .05$; $^{***}p < .01$

Recommendation	$\Delta EBIT(-1)$	$\Delta EBIT(0)$	$\Delta EBIT(1)$
Positive Recommendations			
1. All Reinitiations	0.25***	0.06*	-0.19***
2. *Same Analyst*	*-0.17*	*0.16**	*0.06*
3. *Different Analyst*	*0.32****	*0.02*	*-0.27****
4. Initiations	0.37***	0.04	-0.13*
(2)-(3)	-0.49**	0.14	0.32**
(2)-(4)	-0.53**	0.12	0.18
Upgrades			
5. All Reinitiations	0.19**	0.07***	0.02
6. *Same Analyst*	*-0.27*	*0.18**	*0.26***
7. *Different Analyst*	*0.27****	*0.02***	*-0.04***
8. Regular Upgrades	-0.10***	-0.06*	-0.09***
(6)-(7)	-0.54**	0.16	0.30**
(6)-(8)	-0.17	0.24**	0.36**

Table 1.14 – *Continued from previous page*

Recommendation	$\Delta EBIT(-1)$	$\Delta EBIT(0)$	$\Delta EBIT(1)$
Negative Recommendations			
9. All Reinitiations	-0.30*	-0.43**	-0.03
10. *Same Analyst*	*-0.30*	*-0.90***	*-0.62*
11. *Different Analyst*	*-0.31*	*-0.29*	*0.13*
12. Initiations	-0.43	-0.44**	-0.16
(10)-(11)	0.00	-0.61	-0.75
(11)-(12)	0.13	-0.46	-0.46
Downgrades			
12. All Reinitiations	-0.19***	-0.29***	-0.15***
13. *Same Analyst*	*-0.30***	*-0.42****	*-0.39***
14. *Different Analyst*	*-0.13****	*-0.24****	*-0.06***
15. Regular Downgrades	-0.09**	-0.40***	-0.19***
(13)-(14)	-0.17	-0.18	-0.33
(13)-(15)	-0.21**	-0.02	-0.20

Taken together, these two tables support the idea that analysts who reinitiate the coverage of firms they previously covered have the ability to select those with superior future operating performance. I also checked (untabulated results) that reinitiations by the same analyst did not start to outperform the market before the analyst issued its reinitiation: in the three months that precede the reinitiation announcement date, the mean CAR for reinitiations by the same analyst reaches 0.21% (t=0.34), and the mean CAR for reinitiation upgrades by the same analyst -0.30% (t= -0.41). In other words, when an analyst reinitiated the coverage of a stock he previously covered, the stock did not outperform in the previous three months, and had not started to go up,[23] but the operating performance of the firm started to go up significantly during the same fiscal year as the reinitiation and in the fol-

[23] Untabulated results show this is also true in the six months before the resumption of coverage.

lowing year too. When a different analyst was assigned to the reinitiation, the situation was a little bit different: the stock price already had already risen in the previous three months (CAR=1.32% and t=4.34 for positive recommendations), and the operating performance had also started to improve since the previous year. In other words, when a broker reinitiates the coverage with a different analyst, he is following a favorable existing trend (the stock price has already started to rise, and operating performance has already been improving). This could also explain why the average three and six-month post announcement CAR were previously found to be stronger for reinitiations by the same analyst than for reinitiations by a different analyst. On the other hand, regular upgrades are not followed by a superior operating performance, and they are only followed by a short-lived asset-pricing effect.

1.7 Conclusion

This paper sheds new light on the information content of analysts' reports. In particular, I show that reinitiations of coverage by the same analyst and reinitiation upgrades have meaningful asset pricing implications that have gone unnoticed so far. The immediate market response to reinitiation upgrades is similar to the immediate market response of regular upgrades. However, this paper highlights several significant differences between the two types of signals: reinitiations by the same analyst and reinitiation upgrades by the same analyst are followed by a significant drift over a six-month horizon that does not revert. On the other hand, regular upgrades are only followed by an immediate market response.

I investigate several explanations. Reinitiations are not the most frequent signal sent to the market and the underreaction could be explained by a gradual diffusion of information in the market. Portfolio sorts on turnover show that the portfolios with the lowest level of initial turnover subsequently display the strongest CAR. I also look at changes in operating performance of the firms subject to a reinitiation of coverage. Indeed, when the same analyst is in charge of the reinitiation, he can use his prior knowledge of the firm to time his recommendation appropriately. I find a significant improvement in profitability both on the year the reinitiation takes place and in the following year, which could result from these analysts' stock-picking and market-timing abilities. Moreover, reinitiations of coverage can be exploited by investors to form a trading strategy that survives transaction costs, in contrast to any other type of recommendation.

Finally, reinitiations are an instance in which financial analysts produce informative reports, in contrast to some of the earlier conclusions of the literature. Future research will explore in greater detail the determinants of reinitiations, as well as the characteristics of analysts who reinitiate. In the context of the debates on market efficiency, my results identify a situation in which the marginal returns of information search dominate its marginal costs, in accordance to the view expressed in [GS80].

1.8 Appendix: [CS12]'s algorithm

In their paper, [CS12] propose a new method to estimate the spread. Their work starts from the idea that the high-low price ratio has two components: a variance component that grows proportionally with time and a spread component which stays constant over two consecutive days. They assume that the high price is buyer initiated and the low price is seller initiated, which means that the actual and observed high and low prices follow the following relationship:

$$[ln(\frac{H_t^O}{L_t^O})^2] = [ln(\frac{H_t^A(1+S/2)}{L_t^A(1-S/2)})]^2$$

where H_t^A L_t^A are the actual high (resp. low) stock price on day t, and H_t^O L_t^O the observed high(resp. low) stock price on that same day.

In order to solve for the two components of the high-low price ratio, they use two equations, the first one involving the high-low price ratio over two consecutive days and the second one with the high-low price ratio over a single two-day estimation window.

They show that the spread S can be estimated as:

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}$$

where α can be estimated with the following closed-form solution:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$$

with

$$\beta = E[\sum_{j=0}^{1}[ln(\frac{H_{t+j}^{O}}{L_{t+j}^{O}})]^2]$$

and

$$\gamma = [ln(\frac{H_{t,t+1}^{O}}{L_{t,t+1}^{O}})]^2]$$

The procedure makes it possible to get an estimate of the spread using only the high and low prices from two consecutive days. Their procedure relies on a small number of assumptions (stock prices follow a diffusion process, volatility grows linearly with time, and spreads are constant over a two-day period), and that stock prices do not change over non-trading periods.

I adjust daily high and low prices for overnight returns: if the low price of day (t+1) is greater than the previous day close, I decrease the day (t+1) low and high price by the amount of the overnight change. If the day (t+1) high is below the day t close, I increase the day (t+1) high and low prices by the amount of the overnight change. Moreover, in some rare instances, the estimate for the spread could be negative. That could take place in periods of high volatility when the volatility over a two-day period is greater than twice the daily volatility or when there is a large price change overnight. If the spread estimate is negative, I set it to zero before computing the monthly average.

For each recommendation in my data, I estimate the spread using any two consecutive trading days on the month the recommendation is issued, and I use the average value as my estimate of the spread.

CHAPTER 2

Are Economic Tracking Portfolios (ETP) useful? And What Fundamentals Are Driving Stock Prices?

2.1 Introduction

If stock returns are partly and differentially influenced by macroeconomic fundamentals, it should be possibly to construct portfolios that track these influences. [BGL89] (henceforth BGL) first showed how to form efficient portfolios that track macroeconomic series. When they projected consumption growth on various investment asset returns, they found that their portfolio tracking consumption growth loaded heavily on junk bonds, transportation stocks, and services stocks. The approach continues to be used, e.g., as in [JW07]. [Lam01] extended the BGL insight by arguing that stock prices are claims on future cash-flows, so changes in stock prices should capture revisions in investors' expectations about future economic conditions. He finds that ETPs constructed from ten industry stock portfolios track changes in investor expectations of excess stock returns, TBills, excess bond returns, inflation, industrial consumption growth, and consumption growth.

Our paper reexamines whether industry-portfolio based ETPs can track the contemporaneous macroeconomic variables used in Lamont, plus real-estate returns, exchange rates, and oil returns. We explore tracking both the series themselves and their Lamont variants (changes in expectations). Unlike BGL and [Lam01], our paper's focus is primarily on out-of-sample forecasting. There are two reasons. First, it is well-known (e.g.[XD07] and [LM90]) that in-sample regressions are more susceptible to spurious correlations and misspecification. Second, investors that want to hedge portfolios against some macro-economic influences are more interested in tracking variables out-of-sample than in-sample. [WG08] show that many familiar in-sample predictors of future stock returns did not hold out-of-sample.

We find that the answer is no. ETPs formed from industry portfolios did not track a variety of interesting macro-economic series better out-of-sample than simple alternative benchmarks, such as a constant zero, the T-Bill, the overall stock market, or a single stock that had the highest past correlation with the target. It is also not a question of whether ETPs are statistically significantly better than simpler benchmark alternatives, but whether they are better, at all. They are not.

Our (lack of) findings are robust. Our paper reports only a small representative set of our specification attempts. For example, we used different success metrics, target variable transformations, conditionings, and investment portfolios (e.g., more or fewer industry portfolios). The findings were consistently negative, and the reader gains little additional insight from seeing the failure in more dimensions than we are reporting here.

We conclude that if there are differential macroeconomic components in industry stock price fluctuations, these components are not strong and stable enough to allow investors to construct ETPs from industry portfolios for the purpose of hedging them out-of-sample. Our macroeconomic series have no stable associations with such stock portfolios. Our findings are also relevant beyond out-of-sample investing. The out-of-sample tests are merely a particular test of an underlying relation. Thus, our findings cast doubt that ETPs can be used in-sample, too. They indicate that the correlation between the macroeconomic bogey and portfolios is due to overfitting. This means that, for example, the use of ETP portfolios to interpolate the daily behavior of these bogeys is spurious. It also raises the deeper question of why there seems to be no stable association between macroeconomic factors and industry stock portfolios. Are industry stock returns more noise than fundamentals? This question is beyond the scope of our paper.

Our paper now proceeds as follows: Section 2.2 describes the data and defines the target variables. Section 2.3 describes the two methods we study; Section 2.4 presents the results; Section 2.5 places the results in perspective and Section 2.6 concludes.

2.2 Data

Table 2.1 lists our variable definitions and their sources. Our dependent variables—the macroeconomic bogeys that we want to track—start with those in [Lam01]): excess stock returns, Treasury Bills, excess bond returns, inflation (CPI), industrial production growth, and consumption growth. In addition, we include real estate returns, some currency returns (Canadian dollar return, Swiss Franc Return, British Pound Return and Japanese Yen Return) and one commodity return (oil). We also tried another commodity (gold) and obtained similar results which are not reported here.

Table 2.1: Data Sources

GFD is global financial data. FHFA is the Federal Housing Finance Agency. ALFRED is the Fed Reserve Bank of St Louis data base. French is Ken French's website. "calc" means calculated. All data is available on the paper's website. All data are from 07/1963-12/2010, except currencies which begin after Bretton-Woods (04/1974). Because there were no one-year government bonds between 09/2001 and 05/2008, we estimated the one-year government yield during the missing years. The full data sample suggested STY $= 0.11 + 0.80 \cdot$ T-bill $+ 0.17 \cdot$ LTY, where STY is the yield of the one-year government bond, and LTY is the yield of the twenty-year government bond. The R^2 was 99%. Similarly, there were no twenty-year government bonds between 01/1987 and 09/1993. We estimated a regression on the full data sample, which gave LTY $= 0.31 - 0.17\ STY + 1.12\ MTY$, where STY is the yield of the one-year government bond, LTY is the yield of the twenty-year government bond and MTY is the yield of the ten-year government bond. The regression R^2 was 99%. [Lam01] used 8 industry portfolios from a commercial data provider, whereas we use the ten Fama-French portfolios.

Series	Source	Description
Panel A: Independent Variables To Form Portfolios		
10 Industry Portfolio Returns	French	[FF97]
Overall Stock Return	French	[FF97]
T-Bill Returns	French	[FF97]
1-Year/10-Year/30-Year Gov Bonds	CRSP	CRSP documentation
Stock Returns	CRSP	(used to find some simple benchmark stocks)

Table 2.1 – *Continued from previous page*

Series	Source	Description
Panel B: Dependent Variables To Hedge		
Excess Stock Return	calculated	difference between the compounded rate of return on the value-weighted stock market index from CRSP and the compounded rate of return on the three-month Tbill. Denoted X.Stock Returns. (Note that our tracker is the S&P500 return, not the value-weighted portfolio.)
Excess Bond Return	calculated	difference between the compounded rate of return on the 20-year government bond and the compounded rate of return on the Tbill
Inflation	BLS / calculated	log-difference in the CPI (NSA)
Industrial growth	ALFRED / calc'd	log-difference in the Industrial Production Index (SA)
Consumption growth	ALFRED / calc'd	log-difference in Personal Consumption Expenditures (SA)
Real Estate return	FHFA	log-difference in the House Price Index (NSA)
Exchange rates	GFD	log-differences in nominal exchange rates (CAD, SWF, GBP, JPY, all in USD)
Oil return	GFD	log-difference in the West Texas Intermediate (WTI) spot price ($/bl)

Table 2.1 – *Continued from previous page*

Series	Source	Description
Panel C: Control Variables		
3-month Tbill	French	
Short-term premium	ALFRED/calc'd	Difference between the yield on the 1-year government bonds and the Tbill
Medium-term premium	ALFRED/calc'd	Difference between the yield on the 10-year government bonds and the Tbill
Long-term premium	ALFRED/calc'd	Difference between the yield on the 20-year government bonds and the Tbill
Dividend yield	CRSP	12-month dividend yield on the CRSP value-weighted portfolio
Default premium	ALFRED	Baa yield minus AAA yield
12-month excess stock returns	calc'd	Difference between the compounded rate of return on the market and the compounded rate of return on the 3-month Tbill
12-month inflation	calc'd	log difference in the CPI (NSA)
12-month industrial growth	calc'd	log difference in the Industrial Production Index (SA)

Our independent variables are the rates of returns of ETPs constructed from the ten industry portfolios from [FF97], and the one-year, a ten-year, and a twenty-year government bond portfolios (from CRSP). All ten industry portfolios are zero-cost portfolios. In addition, we entertain simpler benchmarks: the monthly S&P stock market return, the T-bill rate, the single stock from the one thousand largest market-cap CRSP firms at the end of the previous month that had the highest correlation with our dependent variables, and combinations of the T-bill rate with the S&P500 or this stock. We allow investors not to be fully invested, i.e., to leave a predetermined part of their wealth under their mattresses, not earning interest.

Table 2.2 lists some descriptive statistics. Panel A shows that our ten industry portfolios have means of around 1% per month and standard deviations of about 5% per month. Our targets in Panel B are divided into those used by [Lam01] and a number of additional targets we are introducing—real-estate returns, exchange rates, and oil price changes. Presumably, the latter should be relatively easier to track, because they are also traded actively on financial markets. The only oddity is the high autocorrelation of the monthly real estate return series. Lamont also relies on overlapping twelve-month variables, which are described in Panel C.

Our sample period is 07/1963-12/2010 for most of our macroeconomic series. However, for currencies, we start only on 04/1974, one year after the beginning of the floating exchange rate period.

Table 2.2: Descriptive statistics

Panel A are the ETP ingredients. In Panels B and C, the first six targets are from [Lam01], the subsequent seven are our's. In Panel A, the variables are defined on a twelve-month horizon, whereas in Panel B, they are defined on a one-month horizon. The data sample ends in 12/2010. Twelve-month changes are overlapping, which explains their high autocorrelation.

Industry	Mean	Median	Sdv	Min	Max	Autocorr	Starts
Panel A: Independent Variables							
Consumer NonDurables Goods	1.07	1.07	4.39	–21.03	18.73	0.11	7/63
Consumer Durables	0.87	0.78	6.29	–32.83	42.84	0.13	7/63
Manufacturing	0.97	1.17	5.00	–27.33	17.51	0.07	7/63
Energy	1.10	0.98	5.38	–18.39	24.29	–0.02	7/63
Business Equipement	0.97	0.98	6.67	–26.15	20.46	0.06	7/63
Telecom	0.83	0.96	4.73	–15.56	22.12	0.04	7/63
Shops	1.01	1.03	5.32	–28.31	25.80	0.14	7/63
Healthcare	1.03	1.07	4.98	–20.47	29.58	–0.00	7/63
Utilities	0.82	0.84	4.10	–12.65	18.80	0.06	7/63
Other	0.92	1.35	5.38	–23.68	20.16	0.14	7/63
Panel B: 1-month variables, Naïve Targets (1-Month Changes)							
Excess Stock Returns	0.45	0.80	4.53	–23.14	16.05	0.09	7/63
Tbill	0.44	0.42	0.24	0.00	1.35	0.96	7/63
Excess Bond Returns	0.19	0.16	2.98	–10.59	14.43	0.04	7/63
Inflation	0.35	0.30	0.36	–1.93	1.79	0.57	7/63
Industrial Production Growth	0.22	0.27	0.76	–4.04	3.04	0.33	7/63
Consumption Growth	0.58	0.57	0.56	–1.99	2.74	–0.08	7/63
Real Estate Return	0.26	0.34	0.57	–2.08	1.46	0.99	1/92
Canadian Dollar Return	0.01	0.01	1.90	–9.04	13.02	–0.05	4/74
Swiss Franc Return	–0.27	–0.17	3.54	–12.87	14.55	0.02	4/74
British Pound Return	0.10	0.10	3.02	–13.58	13.60	0.09	4/74

Table 2.2 – *Continued from previous page*

Industry	Mean	Median	Sdv	Min	Max	Autocorr	Starts
Japanese Yen Return	–0.28	–0.02	3.30	–16.39	10.36	0.04	4/74
ΔOil	0.45	0.15	8.58	–39.12	37.14	0.19	4/74
Panel C: Dependent Variables, Lamont Targets (12-Month Changes)							
Excess Stock Returns	5.77	8.65	17.66	–49.22	58.35	0.92	7/63
Tbill	5.49	5.19	2.85	0.02	15.22	0.99	7/63
Excess Bond Returns	2.32	1.58	11.17	–28.01	51.99	0.91	7/63
Inflation	4.15	3.42	2.75	–2.12	13.76	0.99	7/63
Industrial Production Growth	2.68	3.18	4.72	–13.76	11.82	0.97	7/63
Consumption Growth	6.98	6.82	2.62	–3.54	12.72	0.96	7/63
Real Estate Return	3.51	3.43	4.69	–9.99	10.65	0.99	1/92
Canadian Dollar Return	0.11	0.36	6.62	–21.66	25.71	0.92	4/74
Swiss Franc Return	–2.97	–2.56	12.79	–41.51	27.60	0.92	4/74
British Pound Return	1.23	0.14	11.57	–29.68	32.82	0.93	4/74
Japanese Yen Return	–3.11	–2.94	12.33	–43.65	28.15	0.93	4/74
ΔOil	7.08	4.05	33.63	–99.82	121.45	0.91	4/74

2.3 Methods

2.3.1 Targets

The naïve tracking targets for an investor interested in hedging are the contemporaneous changes (innovations) in the macroeconomic series. At the end of period t, the investor buys the tracking portfolio whose weights are determined only by data available up to that point. The portfolio return between $t+1$ and $t+2$ is then compared to the change in the dependent variable between $t+1$ and $t+2$. The success metric can be either the difference in means or the correlation between the series.

The tracking targets in [Lam01] are more unusual. At the end of each period t, the investor again constructs and buys the tracking portfolio. But the dependent variable (to which the performance of his portfolio is compared to) is not the target performance from $t+1$ to $t+2$, but (usually) the target performance from $t+1$ to $t+12$.

To the extent that the twelve-month change can be decomposed into the one-month change and the following eleven-month change, these targets are the sum of the contemporaneous movement and a prediction of how the targets will perform over the next eleven months. For example, one of Lamont's targets is the CRSP value-weighted portfolio. Its return is roughly the sum of the first month return plus the subsequent twelve months returns. The one-month performance component is easily tracked by any highly diversified stock portfolio, but the subsequent eleven-month performance component is not—it is really a prediction, which is obviously difficult to do with stock returns. Thus, most of the coefficient in the Lamont one-year "excess stock return" prediction comes from the component of the first month that stock portfolios share, not from the return performance in the subsequent eleven months.

2.3.2 ETP Regression Projection

Economic tracking portfolios (ETP) are constructed by running a regression correlating the tracking target with the rates of return on the thirteen tracking assets. (For algebraic details and justifications, consult [Lam01], p.164)

We also follow the choice of *lagged* control variables in [Lam01]. These controls are the three-month Tbill return, the term premium for the twenty-year government bond (defined as the yield on the long-term bond minus the yield on the Tbill), a term premium for the one-year government bonds, the twelve-month dividend yield on the CRSP value weighted aggregate portfolio, a default premium for corporate bonds (Baa yield minus the AAA yield), the twelve-month Industrial production growth, the twelve-month inflation and the twelve-month excess stocks returns. The control variables are both in the estimation regressions and the testing regressions (we could not use Lamont's one-month commercial rate series in the set of control variables, because it was discontinued in 1997).

2.3.3 Simpler Benchmarks

As simpler benchmarks, we entertain four primitives:

- A zero constant.
- The T-bill.
- The highest-return-correlation stock with uninterrupted data, chosen from the one thousand highest-capitalization firms on CRSP. This stock is chosen in-time based on the prevailing sixty-month correlation with the target.
- The S&P500.

The three later assets can consist of only a fraction of the investor's portfolio (as determined by an ex-ante regression on the targets), the rest earning a zero rate of return. We also entertain combinations of the T-bill and the S&P500 or the single-highest return stock. The portfolios of the zero-asset, T-Bill, and single stock are formed in a manner analogous to the way ETPs are formed (i.e., based on ex-ante regressions).

2.4 Results

2.4.1 In-Sample Prediction

Table 2.3 establishes comparability of our results with those in [Lam01]. It shows the in-sample performances of the estimated tracking regressions in the same sample period. In his original paper, [Lam01] used eight industry portfolios and four bond portfolios (one-year, ten-year, thirty-year government bond portfolios, and a credit bond portfolio). Our base assets are similar, but not identical. We use the returns on ten industry portfolios and only three bond portfolios. The return on the credit portfolio was discontinued in 1997.

Table 2.3: In-Sample R2 Performance

The estimation period is 01/1947-12/1994, with the exception of consumption (01/1959-12/1994). In Panel B, we replicate [Lam01]'s regression, albeit with our ten industry plus three bond portfolios, instead of his eight industry plus four bond portfolios. We report both the R^2 from his paper and from our replication. (Note: Following [Lam01], Excess Stock Returns are twelve-month returns, while the tracking portfolios [incl. the S&P500] is a one-month return.)

Panel A: Naïve Targets (1-Month Tracking)

	Financial variables			*Macroeconomic variables*		
	Excess.Stock Returns	T-bill	Excess.Bond Returns	Inflation	Ind.Prod Growth	Cons. Growth
10 ETPs + 3 Bonds	perfect	perfect	perfect	0.37	0.20	0.09
Benchmarks						
Tbill	0.08	perfect	0.06	0.34	0.15	0.06
Tbill + 1 Stock	0.08	perfect	0.06	0.34	0.15	0.06
1 Stock	0.08	perfect	0.06	0.34	0.15	0.06
Tbill+ S&P500	0.98	perfect	0.13	0.34	0.15	0.06
S&P500	0.98	perfect	0.13	0.34	0.15	0.06

Panel B: Lamont Targets (12-month overlapping tracking)

	Financial variables			*Macroeconomic variables*		
	Excess.Stock Returns	T-bill	Excess.Bond Returns	Inflation	Ind.Prod Growth	Cons. Growth
Pfios [Lam01]	0.45	0.91	0.35	0.54	0.45	0.38
Replicated 10 ETPs and 3 Bond	0.44	0.90	0.33	0.54	0.44	0.43
Benchmarks						
Tbill	0.40	0.88	0.27	0.50	0.42	0.41
Tbill + 1 Stock	0.40	0.88	0.27	0.50	0.42	0.41
1 Stock	0.40	0.88	0.27	0.50	0.42	0.41
Tbill+ S&P500	0.41	0.88	0.29	0.50	0.42	0.41
S&P500	0.41	0.88	0.29	0.50	0.42	0.41

In the top panel, we run regressions that explain one-month targets with one-month contemporaneous trackers. Obviously, when the trackers include the target as one of the independent variables, the performance is perfect. The more interesting columns relate to the three macroeconomic variables. With eleven independent variables, the ETPs track better than the simpler benchmarks. We find that the typical R^2 explaining inflation is 0.37 with ETPs instead of the reported 0.34 in [Lam01]. Our typical R^2 explaining industrial production growth is 0.20 instead of the reported 0.15 in [Lam01]. And our typical R^2 explaining consumption growth is 0.09 instead of the reported 0.06 in Lamont.

In the bottom panel, we replicate and extend the results in [Lam01]). Because the trackers are now rates of returns of one-month portfolios while the tracked variables are twelve-month variables, perfect tracking of the target by the portfolios is no longer possible. More important for us, the R^2 from the ETP regression over the identical 1947–1994 sample period match the results in Lamont's paper. As they should, the simpler benchmark portfolios again perform worse in-sample. All in all, we can replicate the findings in [Lam01] in our data quite well.

2.4.2 Out-of-Sample Naïve One-Month Contemporaneous Tracking

Table 2.4 examines a standard tracking portfolio approach, where a contemporaneous portfolio is designed to correlate with its target. The estimation period is sixty months. The out-of-sample prediction occurs in the first subsequent month. Again, some of the results of the table are not interesting, because the ETPs contain the target as one of the independent variables themselves. The evidence suggests that ETPs, consisting of industry portfolios and the three bond portfolios, are incapable of tracking any of the macro-economic series better than simpler benchmarks (except for oil).

Table 2.4: Naïve Target Tracking (One-Month RMSE)

Variables are defined in Table 2.1. The columns are the dependent target variables. The rows are the tracking portfolios. The rolling estimation window is sixty months. The tracking horizon is the first month after the estimation window. The objective metric is the difference between the macroeconomic target variable (typically itself a percent change) and the rate of return on the formed tracking portfolio. Following [Lam01], lagged z variables (Panel C of Table 2.1) are used in the prediction equation, but not the fitting equation. By repeating this exercise month after month, we obtain a time-series of forecast errors. This table reports their RMSE. The best (lowest-RMSE) tracking portfolio is boldfaced. If a portfolio has a lower RMSE than the zero forecast, we test the forecasting ability with the [DM95] against this null prediction. The "1 Stock" is the one stock from CRSP's one thousand largest stocks that correlated best in the estimation period with the target. The sample is 07/1963 to 12/2010. The first prediction occurs in 07/1968 (except for the currencies), the last in 12/2010.

	Lamont Targets →						Other Targets →					
Trackers ↓	X.Stock Returns	T.Bill Returns	X.Bond Returns	Inflation Rate	Ind.Prod Growth	Cons. Growth	Real Estate	USD CAD	USD SWF	USD GBP	USD JPY	Oil Return
	No Controls											
10 ETPs + 3 Bonds	0.00	0.52	0.00	0.57	0.94	0.85	0.68	1.83	3.66	3.21	3.78	8.77**
10 ETPs	0.00	0.52	3.09	0.55	0.89	0.83	0.68	1.76	3.69	3.15	3.80	**8.21****
	With z Controls											
10 ETPs + 3 Bonds	0.00	0.52	0.00	0.58	0.91	0.87	0.68	1.87	3.73	3.34	3.88	8.87***
10 ETPs	0.00	0.52	3.05	0.56	0.87	0.84	0.68	1.76	3.88	3.21	3.92	8.41***
Zero Forecast	4.70	0.52	3.11	0.52	**0.77**	0.79	0.69	1.96	3.49	3.05	**3.39**	9.21
	Without z Controls											
Tbill	4.74	0.00	3.13	**0.32*****	0.78	**0.57*****	0.64	1.97	3.52	3.08	3.43	9.27
Tbill+1 Stock	2.83***	0.00	2.71**	0.34***	0.79	**0.57*****	0.72	2.10	3.68	3.22	3.75	8.76
1 Stock	2.78***	0.52	2.71**	0.55	0.84	0.83	0.72	2.08	3.62	3.19	3.68	8.67
Tbill+S&P500	**0.76*****	0.00	3.07	0.33***	0.78	**0.57*****	0.65	1.70**	3.50	3.07	3.47	9.20
S&P500	0.94***	0.52	3.04	0.52	0.79	0.79	0.69	**1.69****	**3.47**	**3.04**	3.44	9.14

Table 2.4 – *Continued from previous page*

	Lamont Targets →						Other Targets →					
Trackers ↓	X.Stock Returns	T.Bill Returns	X.Bond Returns	Inflation Rate	Ind.Prod Growth	Cons. Growth	Real Estate	USD CAD	USD SWF	USD GBP	USD JPY	Oil Return
	With z Controls											
Tbill.	9.12	0.00	6.86	0.52	1.21	1.23	**0.62***	2.71	5.97	5.13	4.95	15.17
Tbill+1 Stock.	5.13	0.00	4.28	0.63	1.08	2.09	0.69	2.88	5.36	5.20	5.10	13.75
1 Stock.	2.39***	**0.48**	**1.19*****	0.53	**0.24*****	1.22	0.69	2.10	3.65	3.23	3.73	8.70
Tbill+SP500.	1.24***	0.00	7.26	0.53	1.26	1.25	0.63*	2.42	5.88	5.21	4.95	15.30
SP500.	0.94***	0.52	3.04	0.52	0.78	0.80	0.69	1.70**	**3.47**	3.06	3.41	9.25

- Inflation: It may not be surprising that the T-bill tracks inflation better than the ETPs (despite their inclusion of the bond portfolios). However, the ETPs cannot even beat the zero forecast.
- Industrial Production growth: The zero-forecast and T-bill forecast outperform the ETPs. The Tbill combined with either one stock or the S&P500 performs just as well.
- Consumption growth: The zero-forecast, T-bill, T-bill plus stock, and T-bill plus S&P500 all outperform the ETPs.
- Real Estate: Any portfolios with T-bills outperform the ETPs. The zero forecast performs just as well. (However, as already noted, the target has high autocorrelation.)
- Canadian Dollar Exchange Rate: The ETPs outperform.
- Swiss Franc Exchange Rate: The zero-forecast and the T-bill based forecasts outperform the ETPs.
- British Pound Exchange Rate: The zero-forecast and the T-bill based forecasts outperform the ETPs.
- Japanese Yen Exchange Rate: The zero-forecast and the T-bill based forecasts outperform the ETPs.
- Oil Return: This is the only case where the ETP outperforms the other benchmarks.

2.4.3 Long-Term (Twelve-Month) Prediction, Real-Time Implementable

[Lam01] argues that long-term tracking is likely to be more successful than short-term tracking. Table 2.5 replicates the [Lam01] approach. The dependent variable is now a twelve-month cumulative target. To keep in line with [Lam01], the prediction equation lags the independent variable (the target) relative to the estimation equation. In the prediction equation, the independent variables (the tracking portfolios) thus consist of one month of tracking and eleven months of prediction. However, keeping the timing of the two exactly the same leads to virtually identical results.

The evidence in Table 2.5 again suggests that ETPs, consisting of industry portfolios and the three-bond portfolios, are incapable of tracking any of the macro-economic series better than simpler benchmarks.

- Excess Stock Returns: Every alternative simple tracker performs better than the ETPs.
- Treasury Bill Returns: Any portfolio that contains the T-bill return, which matches the one overlapping period of the twelve-months in the dependent variable, outperforms the ETPs. More importantly, the zero-forecast performs just as well as the ETPs. It is slightly better than the thirteen-portfolio ETP set and slightly worse than the ten-portfolio ETP set.
- Excess Bond Returns: Every alternative simple tracker performs better than the ETPs.
- Inflation: The T-bill tracks inflation better than the ETPs (despite their inclusion of the bond portfolios). However, the ETPs cannot reliably beat the zero forecast.
- Industrial Production growth: The zero-forecast and all T-bill-including benchmark portfolios outperform the ETPs.
- Consumption growth: The zero-forecast, T-bill, T-bill plus stock, and T-bill plus S&P500 all outperform the ETPs.
- Real Estate: Any portfolio with T-bills and the zero-forecast outperform the ETPs.
- Canadian Dollar Exchange Rate: Any portfolios with T-bills and the zero-forecast outperform the ETPs.
- Swiss Franc Exchange Rate: With the exception of the one-stock benchmark, the other five benchmarks all outperform the ETPs.

- British Pound Exchange Rate: With the exception of the one-stock benchmark, the other five benchmarks all outperform the ETPs.

- Japanese Yen Exchange Rate: With the exception of the one-stock benchmark, the other five benchmarks all outperform the ETPs.

- Oil Return: All benchmarks outperform the ETPs.

Table 2.5: Twelve-Month Target Tracking, Investable Specification

$$\textbf{Fitting Equation, } t \in [1:60]\textbf{:} \quad \left[\prod_{i=t+1}^{t+12} y_i\right] = f \cdot (x_t, z_{t-1}) \qquad \textbf{First Residual in RMSE:} \quad \left[\prod_{i=73}^{84} y_i\right] - \left[\hat{f} \cdot (x_{73})\right]$$

Variables are defined in Table 2.1. This table is identical to Table 4, except that the dependent variable is a twelve-month ahead cumulated variable, while the independent variable is a one-month portfolio. This is the specification most similar in spirit to [Lam01]. In this table, the estimation regression does not include the vector of control variables. The strategy is investable, but the prediction equation is not identical to the forecasting equation. When the dependent variable is defined as a difference in logs, the twelve-month change in the dependent variable is obtained by just summing the monthly changes in the variable.

	Lamont Targets →						Other Targets →					
	X.Stock	T.Bill	X.Bond	Inflation	Ind.Prod	Cons.	Real	USD	USD	USD	USD	Oil
Trackers ↓	Returns	Returns	Returns	Rate	Growth	Growth	Estate	CAD	SWF	GBP	JPY	Return
	No Controls											
10 ETPs + 3 Bonds	27.60	9.38	16.29	7.29	8.13	11.21	10.75	8.51	17.39	14.49	17.91	43.74
10 ETP	27.95	9.58	16.42	7.32	7.79	11.41	11.09	7.98	16.63	14.06	17.09	41.14
	With z Controls											
10 ETPs + 3 Bonds	22.17	6.43	13.47	5.19	5.38	7.43	7.07	7.82	14.48	13.71	15.38	34.95
10 ETPs	21.85	6.40	12.79	5.15	5.35	7.43	7.19	7.59	14.00	13.39	15.08	34.39
Zero Forecast	19.17	6.42	12.02	5.19	5.23	7.43	**6.77**	**6.91**	12.64	**bf 11.56**	**12.41**	**31.17**
Tbill	21.07	**1.34**	13.20	2.83	5.90	3.91^{***}	7.54	7.32	14.18	13.01	13.92	34.90
Tbill+1 Stock	21.08	1.50	13.26	2.87	5.96	$\mathbf{3.89}^{***}$	8.46	7.38	14.11	13.17	14.26	34.75
1 Stock	18.78^{**}	6.24	**11.94**	5.26	5.21	7.46	7.89	7.04	**12.62**	11.74	12.81	31.29
Tbill+S&P500	21.19	1.35	13.46	2.85	5.79	$\mathbf{3.89}^{***}$	7.38	7.31	14.32	13.25	14.07	34.93
S&P500	$\mathbf{18.77}^{**}$	6.40	12.47	5.24	**5.16**	7.43	7.23	6.98	12.98	11.81	12.94	31.80
	With z Controls											
Tbill	29.01	5.53^{***}	23.64	4.95	8.05	7.21	7.54	9.18	19.94	19.60	20.40	43.77
Tbill+1 Stock.	45.75	2.63^{***}	16.48	**2.36**	7.73	5.06	8.88	9.48	20.43	19.99	20.47	47.49

Table 2.5 – *Continued from previous page*

	Lamont Targets →						Other Targets →					
	X.Stock	T.Bill	X.Bond	Inflation	Ind.Prod	Cons.	Real	USD	USD	USD	USD	Oil
Trackers ↓	Returns	Returns	Returns	Rate	Growth	Growth	Estate	CAD	SWF	GBP	JPY	Return
1 Stock.	19.38	6.36	12.20	5.22	5.28	7.48	7.26	6.93	12.43	11.59	12.62	31.77
Tbill+SP500.	29.97	5.55^{***}	23.89	4.97	8.21	7.20	7.10	9.29	19.59	19.56	20.07	43.72
SP500	19.41	6.42	12.05	5.18	5.29	7.43	7.00	6.88	12.49	11.68	12.46	31.19

2.4.4 Robustness Checks

In this section, we try alternative specifications for ETPs by increasing the number of base assets, expanding the length of the estimation window and also test the ability of ETPs to predict changes in target variables.

As explained above, the twelve-month target variables are the sum of the contemporaneous change in the variable (in the first month) and an eleven-month prediction. Table 2.6 specifically studies the ability of ETPs to predict the change in the target variable in the first month. Here, the dependent variable is the one-month ahead macroeconomic variable. ETPs cannot predict the contemporaneous change in the target variables better than our simple benchmark or the zero constant.

Table 2.7 uses a twenty-year estimation window instead of a five-year estimation window. Once again, the ETPs formed from the ten industries have no power and perform worse than our simple benchmarks.

Table 2.8 extends the universe of eligible stock portfolios from ten to thirty industries. However, ETPs do not perform better when the asset-pricing space expands and our simple benchmarks keep on performing better, especially when it comes to the original macroeconomic variables.

Table 2.6: Prediction, One-Month RMSE

Fitting Equation, $t \in [1:60]$**:** $y_{t+1} = f \cdot (x_t)$ **First Residual in RMSE:** $y_{63} - \hat{f} \cdot (x_{62})$

The dependent variable is a one-month ahead variable, and the independent variable is a one-month portfolio. This is an investable strategy, because the prediction coefficient is known at the end of $t = 61$.

	Lamont Targets →						Other Targets →					
Trackers ↓	X.Stock Returns	T.Bill Returns	X.Bond Returns	Inflation Rate	Ind.Prod Growth	Cons. Growth	Real Estate	USD CAD	USD SWF	USD GBP	USD JPY	Oil Return
	No Controls											
10 ETPs + 3 Bonds	5.42	0.60	3.53	0.59	0.96	0.94	0.79	2.27	4.08	3.68	4.17	10.55
10 ETP	5.29	0.60	3.48	0.59	0.91	0.88	0.79	2.21	3.90	3.49	4.08	10.19
	With z Controls											
10 ETPs + 3 Bonds	5.68	0.52	3.70	0.53	0.89	0.88	0.75	2.49	4.31	4.06	4.29	10.99
10 ETP	5.51	0.52	3.60	0.53	0.86	0.86	0.73	2.43	4.08	3.74	4.17	10.48
Zero Forecast	4.70	0.52	3.12	0.52	**0.77**	0.79	0.69	**1.78**	**3.43**	**2.86**	**3.18**	**8.35**
	Without z Controls											
Tbill	4.70	**0.07*****	3.14	0.32***	0.78	**0.58*****	0.63	1.97	3.53	3.09	3.42	9.27
Tbill+1 Stock	4.75	0.07***	3.18	**0.31*****	0.78	0.58***	0.66	1.96	3.62	3.14	3.42	9.24
1 Stock	4.69	0.52	3.15	0.52	0.79	0.79	0.66	1.94	3.59	3.11	3.37	9.17
Tbill+S&P500	4.77	0.07***	3.18	0.33***	0.79	0.57***	0.62	1.99	3.56	3.09	3.45	9.30
S&P500	4.73	0.52	3.16	0.51	0.78	0.77	0.67	1.97	3.52	3.06	3.42	9.20
	With z Controls											
Tbill	8.97	0.40***	7.36	0.43*	1.32	1.24	0.58***	1.94	3.60	3.11	3.39	9.32
Tbill+1 Stock	8.74	0.39***	7.77	0.41**	1.36	1.18	0.67	3.06	5.92	4.93	6.46	11.65
1 Stock	4.73	0.52	3.18	0.51	0.78	0.80	0.67	1.94	3.60	3.11	3.39	9.32
Tbill+SP500.	9.01	0.40***	7.35	0.42**	1.28	1.11	0.60**	3.13	5.76	4.81	6.34	11.71
SP500	4.74	0.52	3.16	0.52	0.79	0.78	0.68	1.97	3.52	3.09	3.40	9.29

Table 2.7: Twelve-Month Target Tracking-Twenty-Year Estimation Window

Same as Table 2.4 but with a twenty-year estimation window instead of a five-year window.

	Lamont Targets →						Other Targets →					
Trackers ↓	X.Stock Returns	T.Bill Returns	X.Bond Returns	Inflation Rate	Ind.Prod Growth	Cons. Growth	Real Estate	USD CAD	USD SWF	USD GBP	USD JPY	Oil Return
	No Controls											
10 ETPs + 3 Bonds	20.08	5.62	**11.23**	3.69	4.67	6.27	NA	8.94	10.44	9.81	11.03	37.25
10 ETPs	20.40	5.73	12.76	3.62	4.55	6.40	NA	8.87	10.46	9.84	11.55	36.99
	With z Controls											
10 ETPs + 3 Bonds	18.26	4.92	11.37	3.13	4.43	5.76	NA	9.04	10.60	9.54	11.29	37.82
10 ETPs	20.54	4.95	12.05	3.17	4.35^{**}	5.76	NA	8.91	10.30	9.61	11.52	37.38
Zero Forecast	18.50	4.91	11.38	3.12	4.42	5.76	NA	8.60	9.90	9.43	10.68	35.94
	Without z Controls											
Tbill	**18.41**	$\mathbf{0.87}^{*}$	11.71	1.76^{**}	4.22	$\mathbf{2.74}^{***}$	NA	**8.57**	10.02	9.45	11.28	35.87
Tbill+1 Stock	18.65	1.03^{**}	11.69	$\mathbf{1.74}^{***}$	4.33	$\mathbf{2.74}^{***}$	NA	8.64	10.03	**8.70**	10.68	35.88
1 Stock	19.37	5.23	11.93	3.08	4.51	5.83	NA	8.67	**9.93**	8.72	**10.37**	35.97
Tbill+S&P500	18.36	0.88^{*}	11.84	1.78^{**}	**4.18**	2.75^{***}	NA	8.60	10.09	9.51	11.27	**35.54**
S&P500	18.65	4.79	12.13	3.05	4.29	5.57	NA	8.63	10.01	9.45	10.73	35.60
	With z Controls											
Tbill	19.96	2.55^{***}	18.08	4.66	8.78	7.55	NA	**8.57**	10.02	9.45	11.28	35.87
Tbill+1 Stock.	26.67	5.50	41.12	7.20	18.60	11.11	NA	8.64	10.03	**8.70**	10.68	35.88
1 Stock.	19.43	4.97	12.02	3.03	4.46	5.81	NA	8.67	**9.93**	8.72	**10.37**	35.97
Tbill+SP500.	20.30	2.52^{***}	17.95	4.64	8.89	7.58	NA	8.60	10.09	9.51	11.27	**35.54**
SP500	19.22	4.89^{***}	12.07	3.11	4.43	5.77	NA	8.63	10.01	9.45	10.73	35.60

Table 2.8: Twelve-Month Target Tracking-Thirty Industries

This is the same as the regression in Table 2.5, except that the fitting and prediction equations are the same. This strategy is investable.

Fitting Equation, $t \in [1:60]$**:** $\left[\prod_{i=t+1}^{t+12} y_i\right] = f \cdot (x_t)$ **First Residual in RMSE:** $\left[\prod_{i=73}^{84} y_i\right] - \left[\hat{f} \cdot (x_{73})\right]$

	Lamont Targets →						Other Targets →					
	X.Stock	T.Bill	X.Bond	Inflation	Ind.Prod	Cons.	Real	USD	USD	USD	USD	Oil
Trackers ↓	Returns	Returns	Returns	Rate	Growth	Growth	Estate	CAD	SWF	GBP	JPY	Return
	No Controls											
10 ETPs + 3 Bonds	35.30	11.29	21.54	9.02	10.25	13.83	11.66	11.96	25.44	21.04	25.45	59.08
10 ETPs	33.06	11.20	20.96	8.70	9.25	13.62	11.32	11.73	24.97	20.55	24.54	57.37
	With z Controls											
10 ETPs + 3 Bonds	26.56	6.49	16.84	5.29	6.83	7.71	8.16	10.03	21.41	17.45	20.87	46.34
10 ETPs	24.91	6.42	16.05	5.15	6.49	7.69	8.16	9.61	22.33	16.87	21.64	44.63
Zero Forecast	19.17	6.42	12.02	5.19	5.23	7.43	**6.77**	**6.91**	12.64	**11.56**	**12.41**	**31.17**
Tbill	21.07	**1.34**	13.20	**2.83**	5.90	3.91***	7.54	7.32	14.18	13.01	13.92	34.90
Tbill+1 Stock	21.08	1.50	13.26	2.87	5.96	**3.89*** **	8.46	7.38	14.11	13.17	14.26	34.75
1 Stock	18.78**	6.24	**11.94**	5.26	5.21	7.46	7.89	7.04	**12.62**	11.74	12.81	31.29
Tbill+S&P500	21.19	1.35	13.46	2.85	5.79	**3.89*** **	7.38	7.31	14.32	13.25	14.07	34.93
S&P500	**18.77** **	6.40	12.47	5.24	**5.16**	7.43	7.23	6.98	12.98	11.81	12.94	31.80

The under-performance of the ETPs seems quite robust. In additional unreported tests, we have also tested what would happen with a perfect knowledge of the control variables. The RMSE of the ETPs improves slightly, but insufficiently to outperform the simple benchmarks or the zero forecast. The poor performance of ETPs could come from the fact that the model is too unstable or too much time has passed between the estimation and prediction window.

2.5 Related Literature

Previous literature has investigated the relation between equity returns and macroeconomic variables in both directions.

One approach has focused on the effects of innovations in macroeconomic variables on stock market valuations. For instance, [CRR86] looked at the influence of economic variables (like industrial production or changes in the risk premium...) on stock prices.

The other strand of the literature has examined the possibility that changes in asset prices announce future changes in macroeconomic variables through two channels: future cash-flows and the discount rate ([Gor62]). [MB38] researched the link between stock prices and future output. More recently, [EM98] found that stock prices can predict US recessions with a one to three quarter horizon. [SW03] show that some asset prices have a marginal predictive content for output growth and inflation in some countries, even though the forecasts are generally unstable.

A few papers have implemented ETPs in some very specific contexts with mixed results. [Hay01] investigated whether ETPs could be used to forecast three variables (inflation, industrial production growth and retail sales growth) in the United Kingdom. He documented a good in-sample tracking ability of ETPs but a poor out-of-sample forecasting ability because of unstable portfolio weights. [JK04] studied the performance of ETPs in the very specific context of a closed economy which relies heavily on one industry (Finland). They found that expanding the base assets beyond the market portfolio and including several industries can help forecast a few macroeconomic variables in-sample.

All these papers looked at a very limited set of target variables, in the context of one country (and sometimes in a closed economy setting), and didn't consider the point of view of an investor who would like to invest in ETPs in real-time.

2.6 Conclusion

Economic Tracking Portfolios were initially built with the hope that a set of base assets could capture valuable information on the future changes in macroeconomic and financial variables.

This paper shows that there is no evidence that ETPs could be any useful at tracking macroeconomic and financial variables out-of-sample. Alternatively, our simple benchmark is both simpler and more reliable. In particular, it outperforms the ETP and the Zero return asset when it comes to tracking excess stock returns, the Tbill, inflation, consumption growth currencies or real estate under a twelve-month horizon. However, it should be acknowledged that the improvement from just tracking the dependent variables with the zero-return asset looks sometimes small.

The inherent endogeneity in the relation between asset returns and economic activity and the difference between the smoothing characteristics of our macroeconomic variables, and the quick response of equities to new information certainly account for the difficulty to find stronger results.

2.7 Appendix

2.7.1 Economic Tracking portfolios (ETP) Algebra

In [Lam01], ETP portfolios are designed to maximize the correlation between the unexpected portfolio returns and the innovation in the target macroeconomic variable. Given a vector of base assets R, the portfolio weights are found by projecting the innovations in the macroeconomic variables y between months t and $t+k$ on unexpected asset returns,

$$\Delta E_t[y_{t+k}] = b \cdot (R_{t-1,t} - E_{t-1}[R_{t-1,t}]) + \eta_t. \tag{2.1}$$

However, both the left hand side and the right hand side are not directly observable. In order to test this equation, [Lam01] assumes a linear relationship between the vector of expected base asset returns and a set of observable control variables Z:

$$E_{t-1}[R_{t-1,t}] = d \cdot Z_{t-1}. \tag{2.2}$$

Then, the author projects the lagged expectation of y on the lagged control variables:

$$E_{t-1}[y_{t+k}] = f \cdot Z_{t-1} + \mu_{t-1}, \tag{2.3}$$

and the future realization of the target variable can be decomposed as

$$y_{t+k} = E_{t-1}[y_{t+k}] + \Delta E_{t-1}[y_{t+k}] + e_{t,t+k} \tag{2.4}$$

Substituting equations 2.1–2.3 into 2.4 leads to the following OLS regression

$$y_{t+k} = b_t R_{t-1,t} + c_t Z_{t-1} + \epsilon_{t,t+k} \tag{2.5}$$

[Lam01] uses this regression to get the portfolio weights for the tracking portfolios.

2.7.2 The [DM95] Test

We have used the RMSE as our accuracy measure. It is also interesting to know whether one forecast is more accurate than another. In other words, we want to test the hypothesis:

$$E[\epsilon_{1,t}^2] = E[\epsilon_{2,t}^2] \ , \tag{2.6}$$

where $\epsilon_{i,t,t+h}^2$ is the forecast error from model i, (i=1,2); or equivalently:

$$E[d_t] = 0 \ , \tag{2.7}$$

where

$$d_t = (\epsilon_{1,t})^2 - (\epsilon_{2,t})^2 \ . \tag{2.8}$$

[DM95] show that the sample mean loss differential $\bar{d} = \dfrac{1}{T}\sum_{i=1}^{T}(d_t)$ is normally distributed, and propose the following statistic S:

$$S = \frac{\bar{d}}{\sqrt{2\pi \widehat{f}_{\bar{d}}(0)}} \xrightarrow[d]{} N(0,1) \ , \tag{2.9}$$

where $\widehat{f}_{\bar{d}}(0)$ estimates the spectral density of the loss differential at frequency 0.

Finally, [XD07] notes that we can easily compute it by regressing the loss differential series on a constant, and correcting for serial correlation.

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