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Does large difference in endowment of information and technology between market actors create a market inefficiency after an analyst's recommendations release?

(Final Undergraduate Dissertation Report)

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Abstract

Efficient Markets Hypothesis is one of the most influential thoughts in Finance Theory. This paper examines changes in outlook for prices of stocks by rating agencies/banks/institutions and whether they generate an inefficiency. I hypothesize that, having a large difference between their information access and execution abilities, the community of investors trading on analysts' recommendations create an inefficiency which can be exploited. The hypothesis was tested on ca 10K simulated trading ideas and generated an excess return (Alpha) of roughly 4 points. Hence, it suggests the presence of the said inefficiency and builds on the work of Kim, Lin and Solvin (Kim, Lin, Solvin, 1997), which concludes that positive returns can be obtained by following analysts' recommendations by analyzing these returns in depth. I conclude that while positive returns can be achieved, they are a result of excessive risk taking and a retail investor behaving as outlined in our strategy is better of investing into a stock market index. The paper ends with a brief discussion of the possibilities for extending the analysis by incorporating NLP algorithms that, while not a part of this paper, can offer a much richer insight into the matter.

1 Literature review

1.1 Introduction

Forecastability of asset prices has been a topic of interest ever since it became possible to speculate on them, with well-known cases of masses betting on price of an asset moving in a particular direction. Perhaps the most well-know case of this would be the Dutch tulip mania, one of the most famous bubbles. While the primary driver of sky-high tulip bubbles was undoubtedly the belief that they could be later sold for profit, there's a small number of other interesting explanations that provide deeper insight into not only extreme situations like this one, but also to common workings of the financial market. My favorite one would be the argument that the risk appetite of Dutch citizens was arbitrarily high at the time, as it was relatively common that they were risking getting a number of deadly diseases. So the seemingly irrational behavior could have made a lot of sense for these people - a short lifetime expectancy means short-term thinking is understandable, even optimal in some cases. So before I dive into defining my research question and reviewing the work already done on the matter, this is where I want to already hint where we'll be heading later. That is, rather than looking at market(s) from the outside and assessing it as a complex entity; I'll try picking a subset of actors whose actions would be optimal for them, but not consistent with acting as a rational investor. So, in essence, my analysis would be somewhat similar to looking at the group of terminally ill speculators at the time of the tulip mania, seeing what we can learn from them and the way they influence the market.

1.2 Broader context

Though people have been speculating on stock market movements for hundreds of years, it wasn't until relatively recently that they started asking if it's possible to make money doing it. That is, consistently generate profit. Eugene Fama is widely thought to have inspired most work on this. His PhD thesis found only a very small correlation between subsequent daily stock market returns (Shiller, 2013). This was strenghtened by Fama's other work and a number of other publications; with the entire effort later becoming known as the 'Efficient Markets Theory'. What this theory essentially boils down to, is that since the market reacts only to genuine news (with expected news already being 'priced in'), and these are unpredictable, it's impossible to make money consistently by speculating on stock market prices. That is, without having inside information. There are three 'forms' of the Efficient Markets Hypothesis, the strongest one even stating that even inside (private) information is reflected in market prices (Jensen, 1978). What this would imply is that even having this inside information wouldn't allow a speculator to make a profit trading the relevant security. Though this extreme form was never adopted widely, it goes to show just how big the shift in thinking was – we went from taking for granted that it was possible to profit trading assets to almost saying this can't be the case.

Fama eventually ended up receiving a Nobel price, and, somewhat ironically, sharing the honor with professor Shiller. Ironically because while it was awarded for their work on Efficient Markets Theory (EMT); Shiller was one of the biggest (if not the biggest) contributor to disproving the EMT. Perhaps his most notable finding on this was that asset prices move too much to be justified by solely changes in dividends (Shiller, 1981). The reason why a change in dividends should be the driver of an asset price is relatively intuitive – this is the only kind of return an investor ever gets on an asset. Of course, there is also the kind of speculative return she'd get by betting it would increase in value so that it can be sold for profit. Given it pays no dividends however, there is no actual return to be made from profit sharing and the only kind of investor willing to buy such asset would be who doesn't have this information. Even changes in profitability of company's efforts aren't fully indicative of the fundamental share value – should this profit never be returned to investors, there's no real reason for share price to increase. For these reasons, it makes a lot of intuitive sense to look at changes in dividends as a key driver of asset prices.

So, thanks to Shiller's work; both the community of economists and institutional investors mostly believe markets are inefficient. But we're not quite back to where we've been at the beginning of the journey. Thanks to modern technology, up to 70 percent of stock market transactions volume is generated by High Frequency Trading (Lattemann, 2012). This number is now likely considerably higher, since the publication is 6 years old. Combine this with advances in Natural Language Processing, and it becomes clear very quickly just how incredibly hard would it be to trade, say changes in interest rate manually. Even for professional traders at large institutions, who don't have the necessary automation tools at disposal, taking a couple of seconds for a human to read and comprehend the news seems borderline unnecessary. That is, for making the relevant trade.

That being said, an utter inability of institutions to make excess returns on financial markets is far from reality. One intuitive explanation of this would be that someone has to be incentivized to keep the markets efficient. But there's now much more competition, which had to do with increased availability of high-tech computing solutions. HFT profits have been declining as a result. Another one would be that there's still a part of the market behaving irrationally. Another part of the market can than make money by responding to such inefficiencies optimally (Stiglitz, 1981).

1.3 Narrowing down the inefficiency, research questions and resources

As hinted at the start of this review, I want to attempt picking a part of the market where I'm able to hypothesize it will behave differently than a rational, risk-adjusted return maximizing investor. It's no secret that institutions have large teams of professionals focusing on gathering detailed market data and providing the best market intelligence possible. As a consequence, we can expect these 'smart-money' institutions to make more qualified decisions and systematically gain larger profits than ordinary retail investors. This 'smart-money' effect has been documented in various publications, such as (Sapp,2004); who examined this at the level of mutual funds. What I didn't find was something that I had been curious about a long time ago: can we systematically isolate some group of investors where we can estimate the extent to which they decide optimally? Say that we have a knowledge of this happening. Than in the case of a large number of unqualified people deciding to purchase/short sell a security; we know that we'll move away from the price this asset was given under efficient markets – we have discovered an inefficiency! I will explore throughout my dissertation what we can find about this inefficiency and build a trading strategy to illustrate that it can (can't) be exploited.

In more concrete terms, I will analyze asset price changes after analysts that announce their findings publicly change their recommendations. This is where the not so smart money comes in and makes all kinds of trades reflecting the announcements. Moving away from the optimal price, generating some space to correct for this by stepping in the opposite direction some time after retail investors have had the opportunity to make a trade. This essentially outlines the work necessary to test my hypothesis:

1) Obtain Analyst recommendations. Although I'm unsure how deep this analysis will allow me to dive into this, I have already found a website (finviz.com) that aggregates these recommendations by share ticker. So what's left to do here would be to write a script to scrape the website and store it somewhere in an organized fashion.
2) Test the effects. This is where I expect to put in most effort and includes writing a program to analyze historical stock market data combined with the dataset described in point 1. A service called Quantopian provides a free python API for this and so far this is my number one choice. This further requires parametrizing the problem somehow, more specifically find out when we want to make the trade in the opposite direction (how long after the analyst changes outlook), and how long we want to remain in that position. These are hyperparameters, but the problem can be made easier by looking at some measure of risk-adjusted return and try picking values of these that

maximize this measure. This would put us in the position where we have an 'optimal' way to exploit this inefficiency.

3) Further analysis. This is relatively hard to specify without being at an intermediate stage of the analysis, but it may be interesting to segment the effects of interest by say, reputation of the analyst, the relative amount an asset is expected to appreciate/depreciate by, etc.

1.4 directly comparable work

For additional intuition, I chose to discuss 3 papers with focus very close to that of mine. Paper 1 (Womack, 1996) sets the ground for answering research questions such as mine by providing broader context, and is cited by close to every publication I've read on the subject. Paper 2 (Kim, Lin, Slovin, 1997) was published shortly after and extended Womack's work by focusing on the mechanism that describes the way news are incorporated into price. The final paper (Moshirian, Ng, Wu, 2008) is closest to my work and examines the effect of analysts' recommendations on stock prices in emerging markets.

Paper 1

The most important finding Womack arrives at, and the one that's being cited by most papers written later, is that analysts have stock-picking abilities. After release of a recommendation, he reports a price move consistent with the recommendation, a (average) 3% increase in share price for buy recommendations and a much larger 4.7% decrease for sell recommendations. The paper also states that, at least at the time of publication, there was a greater (further unspecified) cost of publishing a sell recommendation that buy. As a result, there's a large positive bias for recommendations, with the ratio of buys to sells being approximately 7 : 1. For reference, my dataset, which starts 20 years later has this bias too. But it has diminished greatly, with roughly 61% of recommendations in my dataset being 'buy'.

What this publication lacked was examination of tradability of this – i.e. can any money be made by following the recommendations. Rather than that, it focused purely on price movements. The problem with that is that there are moments where an asset is illiquid, the so called price gaps. See below the point in May, where shares of Sainsbury's couldn't be bought for a brief time. This is because there was a large positive surprise that made the share appreciate so rapidly that, at the given time, nobody wanted to sell their shares.

Figure 1: Sainsbury's price gap

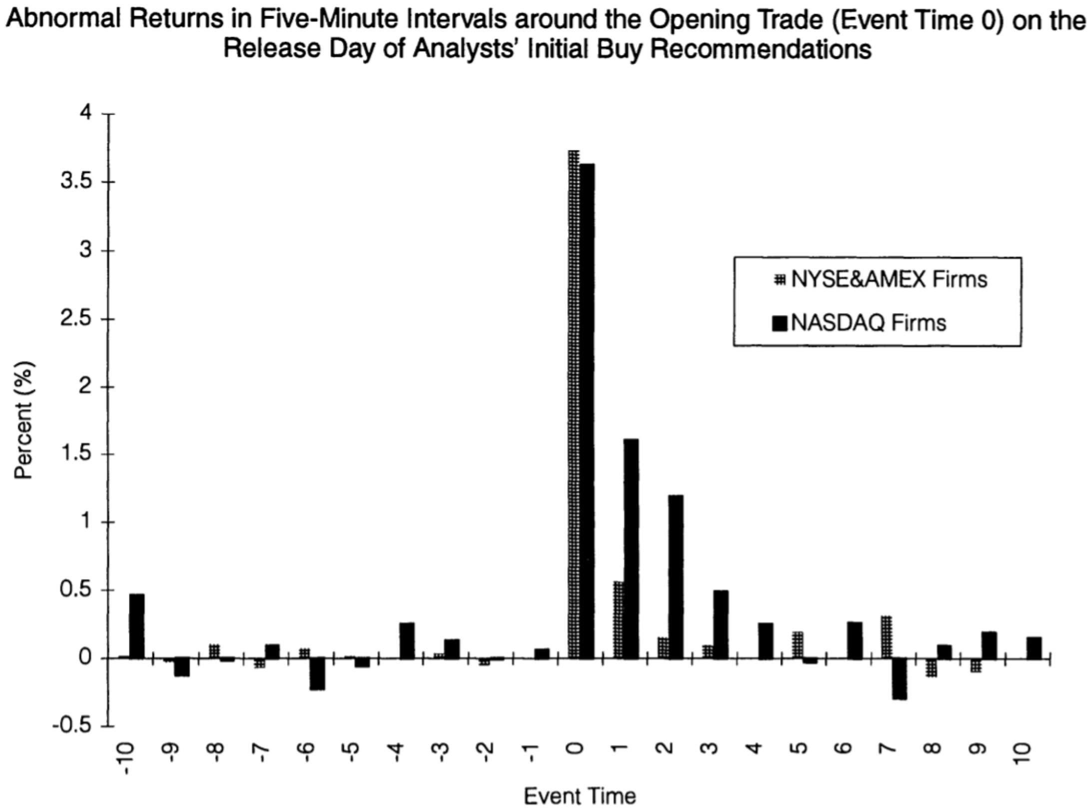
This is incredibly relevant because analysts' recommendations releases can often have an impact so large that a price gap is created and the gains that can be made are different from just the price difference – if you wanted to buy Sainsbury's shares after the announcement, you could only do so at around 310, while the paper works with the initial ~270. So a fuller picture can be offered by taking this into account.

Paper 2

The paper by Kim, Lin and Solvin makes the above described extension and computes magnitude of the effect starting on the first open' i.e. would have considered the price level of 310 above as their starting point. Further, it recognizes the informed traders as the clients of the recommendation issuers and hypothesizes that they have priority access to the recommendations and are able to trade on it before the public can. So it divides the price responses into pre-release (client-generated) and the post released (caused by public). This is one of the ideas I use later to construct my hypothesis about the presence of what I call the 'second inefficiency'.

As far as whether public can make (excess) gains following the recommendation, the paper looks at two microstructurally different markets. It rejects the possibility at one of them (NYSE/AMEX) and accepts it for the other one (NASDAQ). The inefficiency vanishes quickly, (recall this was written in '97), and within 5 minutes, it's virtually non-present.

Figure 2: Excess returns on following analysts' recommendations in 1997. Source: **Kim, Lin and Solvin**



This is what I took most from the paper, even 20 years ago, it was very hard to make profits following recommendations. It is one of the reasons I gave my analysis a slightly different focus, as the reader is able to see in later sections.

Lastly, the dataset authors used here was very small, at least by Today's standard. They've used only 87 observations to calculate the relevant effects. Although it's not impossible to extract meaningful insights from this kind of dataset (and they obtained 1% CL), it's virtually impossible to, say do add another dimension to the analysis such as size of the company and look at the inefficiency as a function of the said size (market capitalization)

Paper 3

The paper by Moshirian, Ng and Wu chose to analyze emerging markets, as opposed to the US stock market picked by the first two publications. It is often difficult to invest in emerging markets, since it is harder to predict the economic situation (possible nationalization of companies) and the overall landscape. The authors argue that this is the reason why the effect of recommendations is greater, even larger than the effect documented by Womack (paper 1). Here, it's worth noting this paper was published 10 years earlier. They have a large (37 000 recommendations) dataset and were able to confirm their hypothesis.

What I disliked was their methodology. More specifically, they measure the price effect by what they call BHAR (buy and hold abnormal returns), defined as:

$$\mathbf{BHAR_T} = \prod_{t=1}^{T}(\mathbf{1} + \boldsymbol{ERit}) - \prod_{t=1}^{T}(\mathbf{1} + \boldsymbol{CRjt})$$

, where $ERit$ is the return at time t if the recommended firm and $CRjt$ is the return of the 'control firm' – a firm comparable to i. This to a certain extent de-trends the effect – i.e. if the control firm and firm I both rose in price, we obtain the effect net of the general price rise and are left with the part of the price increase attributable to the recommendation release. Besides all that, they don't take risk into account anywhere and that is of critical importance as I'll demonstrate throughout the paper. The return on following the recommendation might be fully due to risk-taking; and I arrive at this precise conclusion in my analysis. I later use market Alpha derived from Capital Asset Pricing Model to arrive at (hopefully) more precise estimates of this announcement effect, and also the 'second inefficiency' that I hypothesize to be present, and elaborate on later.

In my quest to explore the extent to which markets are efficient, I decided to construct a particular trading strategy to test my hypothesis that analysts announcing their outlooks to the public is something that generates a market inefficiency. Even though I'm curious about the results of this given strategy, I intend this to demonstrate something broader – large disparities in resources of institutional and retail investors resulting in some kind of polarization – rather than the market being more or less homogenous in terms of expertise of participants, it resembles the situation in the paper by Stiglitz.

If the scope of this work allows this, it may also be interesting to try find a game-theoretical model to explain when and if the group of analysts mentioned throughout this report have an incentive to make their research publicly available when the information they provide is still 'tradeable'.

2 Empirical work

2.1 Data collection and the dataset

After an initial research into what data is available, I decided to use an asset screening site finviz.com, which tracks information about a wide range of securities. This includes the ratings data necessary to test my hypothesis. The relevant data can be seen in the middle section of the screenshot below – date, institution/individual that wrote the recommendation and the change in expected price (last column). So, if we see (second row of the last column) $5 -> $2, this indicates the recommendation(outlook) changed from the target price of 2$ to 5$. It should also be noted only dates are available, rather than a timestamp.

Figure 3: Source data for one of the companies

Sales	**0.04M**	P/S	**141.88**	EPS this Y	**-9.80%**	Inst Trans	**-8.75%**	Short Ratio
Book/sh	**5.21**	P/B	**1.48**	EPS next Y	-	ROA	**-137.30%**	Target Price
Cash/sh	**3.38**	P/C	**2.28**	EPS next 5Y	-	ROE	**-160.30%**	52W Range
Dividend	-	P/FCF	-	EPS past 5Y	**-12.90%**	ROI	-	52W High
Dividend %	-	Quick Ratio	**3.00**	Sales past 5Y	-	Gross Margin	-	52W Low
Employees	**9**	Current Ratio	**3.00**	Sales Q/Q	-	Oper. Margin	-	RSI (14)
Optionable	**No**	Debt/Eq	**0.00**	EPS Q/Q	**-8.60%**	Profit Margin	-	Rel Volume
Shortable	**Yes**	LT Debt/Eq	**0.00**	Earnings	**Mar 07 BMO**	Payout	-	Avg Volume
Recom	-	SMA20	**259.93%**	SMA50	**169.31%**	SMA200	**-55.68%**	Volume

Nov-13-17	**Reiterated**	H.C. Wainwright	Buy	$4.50 → $1
Aug-10-16	**Reiterated**	Maxim Group	Buy	$5 → $2
Apr-18-16	**Initiated**	Rodman & Renshaw	Buy	$5
Jun-02-14	**Resumed**	Maxim Group	Buy	$5
May-09-14	**Initiated**	Maxim Group	Buy	$5

Feb-28-19 08:00AM	Bio-Path Holdings to Present Data at the 2019 AACR Annual Meeting GlobeNewswire +28.71%
Jan-24-19 04:30PM	Stonegate Capital Partners Updates Coverage on Bio-Path Holdings, Inc. (NASDAQ: BPTH) ACCESSWIRE
Jan-23-19 04:01PM	Bio-Path Holdings, Inc. Announces Closing of $1.7 Million Registered Direct Offering Priced At-the-Market GlobeNewswire +10.50%
Jan-18-19 12:31PM	Bio-Path Holdings, Inc. Announces $1.7 Million Registered Direct Offering Priced At-the-Market GlobeNewswire -30.56%
08:00AM	Bio-Path Holdings Announces 1-for-20 Reverse Stock Split GlobeNewswire
Jan-17-19 04:07PM	Bio-Path Holdings, Inc. Announces Closing of Public Offering of Common Stock GlobeNewswire
Jan-16-19 08:24AM	The Daily Biotech Pulse: Revance Common Stock Offering, Adcom Catalyst For Amgen Benzinga
Jan-14-19 10:23PM	Bio-Path Holdings, Inc. Announces Pricing of Public Offering of Common Stock GlobeNewswire -12.96%
04:01PM	Bio-Path Holdings, Inc. Announces Proposed Public Offering of Common Stock GlobeNewswire

So in principle, the most difficult work has been done for us by the screener already – gathering recommendations from thousands of publishers on the web and putting it in one place. It is, however, still far away from being a usable dataset. The site doesn't offer an API that would enable me to easily retrieve the data, so I needed to develop a program that scrapes the site.

I divided the (programming) work on the dissertation into three layers – the first one being a script for making requests to the website, parsing the raw .html files returned and inputing the data of interest into a .csv file that would become our dataset. This has to be done iteratively for every security we're interested in, after figuring out the structure of the website (knowing where on the potentially millions of subsites to look for what we need). Although a large part of all the effort that went into this project was spent on this, I don't discuss it further in the paper, as it's of no economic importance. That being said, the python code developed for this is available (as all the other code/computations) in a GitHub repository created for the project – the file responsible for obtaining a clean dataset from the above described data is **finviz_data.py**.

After running **finviz_data.py**, we obtain recommendations for our 3000 stocks:

Figure 4: A view of the cleaned dataset

	A	B	C	D	E	
1	symbol	date_R	advisor	before	after	idea
2	A	Nov-21-17	Cleveland Researc	67	$71	sell
3	A	Jan-04-17	Overweight	48	$51	sell
4	A	May-17-16	Neutral	46	$51	sell
5	A	May-17-16	Wells Fargo	42	$45	sell
6	A	Jan-07-16	Market Perform -	41	$44	sell
7	A	Dec-09-15	Equal-Weight → C	45	$48	sell
8	A	Nov-17-15	Buy	44	$41	buy
9	A	Nov-04-14	Equal Weight → C	59	$42	buy
10	AA	Dec-20-18	Neutral → Buy	50	$49	buy
11	AA	Sep-25-18	B. Riley FBR	65	$58	buy
12	AA	Sep-12-18	Credit Suisse	48	$50	sell
13	AA	Jul-19-18	Outperform	69	$65	buy
14	AA	Apr-19-18	B. Riley FBR	51	$67	sell
15	AA	Feb-05-18	Credit Suisse	68	$71	sell
16	AA	Jan-18-18	Outperform	51	$59	sell
17	AA	Jan-18-18	Jefferies	67	$63	buy
18	AA	Oct-04-17	Citigroup	57	$60	sell
19	AA	Mar-31-17	Neutral	35	$45	sell
20	AAN	Jul-31-17	Neutral → Buy	40	$55	sell
21	AAN	Nov-02-15	Stifel	45	$32.50	buy

The symbol column contains the ticker (Apple Inc. - AAPL). We further have available the columns I call **before** and **after**, they respectively correspond for targets set on the recommendation prior to the current one, and the current recommendation. Lastly, I also collect the information on what institution made the recommendation, e.g. Credit Suisse. Overall, 12340 distinct recommendations were obtained this way.

2.2 Narrowing down the research question

Having obtained the dataset, it's time to define the trading strategy we'll be building. For each of the ideas (rows in the file above), we'll place an order of 1 share in the direction opposite to that of the recommendation (so the first row in figure two indicating an increase in the target price for by 4$ would be a signal to sell). This is always done at 00:00 of the day following the date the recommendation was issued. This brings out (at least) three questions:

(1) Why trade on the day after?

This is because of the kind of data obtainable from the site. The date they track doesn't contain a timestamp so there's no way of knowing when exactly the recommendation was released. The only way to guarantee there's no look-ahead bias (trading on future information) is placing an order at the beginning of the following day.

(2) Why is this a sell signal?

Having read about advances in Natural Language Processing (NLP) (Zhang, Skiena, 2010) and High Freqency Trading (HFT) lead me to hypothesize it's close to impossible for a retail investor to make profits trading in the direction of news. An example of that would be a small investor reading about an upwards revision of profit expectations. She'd then predict this translates into a higher future price of the company's shares and place a buy order on the security to take advantage of this. Little does she know of the sophisticated language processing technology running on powerful hardware, that was able to 'read' the news and act on them in milliseconds. Since it makes sense that the researcher developing this technology uses it to its full earning potential – i.e. trades until no more profit can be made and price already reflects the news; an additional order coming from the retail investor seconds to hours later will create another inefficiency – in the opposite direction to the original one. This is simply because a buy order on our toy example (still the first row of the dataset) generates an increase in price beyond the appropriate (efficient markets) response that the language processing developer took care of before. Ergo, **we trade in the opposite direction to address this second inefficiency that I hypothesize is present.**

(3) Why trade one share?

This is simply because the back testing program I wrote is already complicated and consumes a lot of my very limited computational resources. It, however, shouldn't matter too much, as assuming share price is exogenous to the results of the strategy. The only relevant argument against this that I came up with is that successful (large) companies tend to have shares that are expensive. But even this is mitigated to certain extent via stock splits. That is, a company may issue new shares that they proportionally distribute to their shareholders, reducing price of one unit of the stock without a change in any of the shareholder's wealth. This is typically done in a discretionary way after price of company's stock reaches certain level – both Google and Apple did this at some point.

Each position opened is held for one week and then closed regardless of what happened to the price in between. I experimented with longer holding periods, but one week turned out sufficient (holding the positions further didn't capture more of the inefficiency and simply introduced unnecessary volatility). Another argument for a relatively short holding period is

Now that we know the strategy, we can outline the questions we'll be able to answer:

(1) Can profit (net of transactions costs) be made by trading on recommendations of analysts?

If we're able to confirm this, the hypothesis about the 'second inefficiency' referred to above will be rejected. There's also publications (Womack, 1996) that examine this, so we should be able to verify if our analysis is consistent with findings of those authors.

(2) Is trading on the day after too late?

Any kind of inefficiency may be momentary and with the strategy being restricted to trading on the day after, it's possible to find no insights because of the missing timestamp.

(3) An extension of the above – what kind of profits (losses) did we obtain?

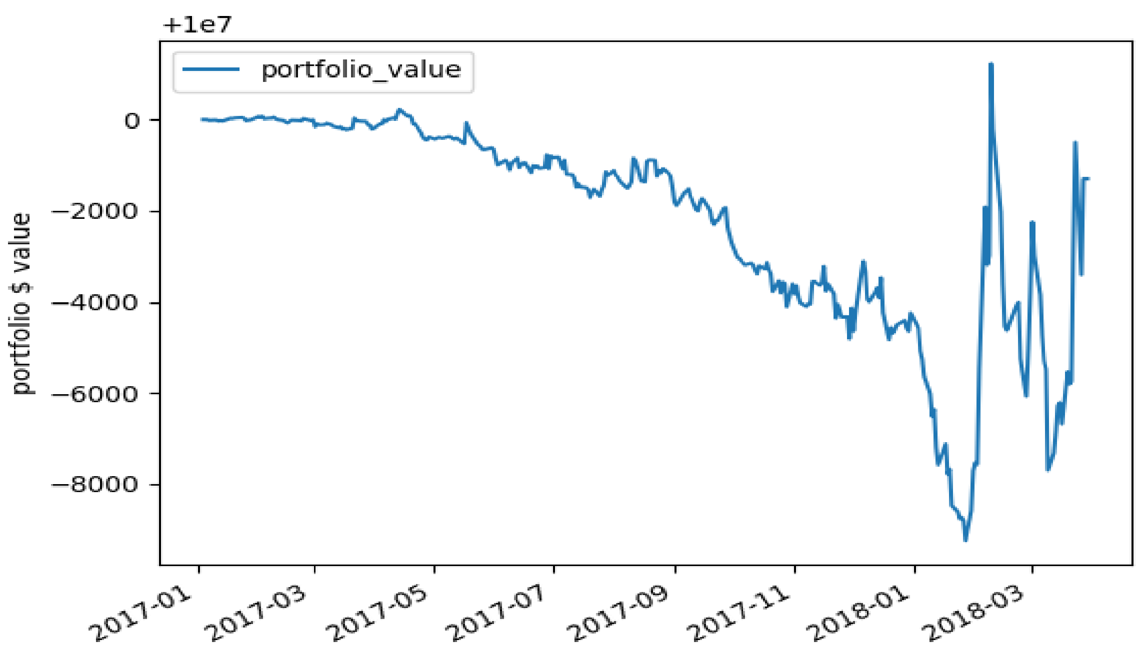
Analyzing the results allowed me to extend the idea further and look at excess returns – something that builds both on my hypothesis and current literature.

3 Results and analysis

3.1 Initial results

Formalizing the above described strategy in **strat.py**, I was able to trade around 95% of the trading ideas in the dataset. The remaining 5% were symbols that the module I used for building the strategy and the backtest (Quantopian zipline) didn't support. I also had to end in March 2018, which is the date the free price data I tested the strategy on ended. Nevertheless, we still have a relatively large sample of trades. So, how did the strategy do? A time-series of portfolio value can be seen below:

Figure 5: Simulated portfolio performance



We can see two things immediately:

(1) The strategy generated a small loss.

(2) – The returns are getting increasingly volatile over time.

While I discuss (1) at length later, the explanation for (2) is relatively simple. The data source only seems to publish the last few recommendations and discards the old ones. So, the more popular the company amongst analysts, the more recent the last recommendation is. Thus the progressively increasing volatility.

As for the analysis of returns, my first idea was to cluster the returns by institution that issued the recommendation and also why I collected it into the dataset in the first place. While that could be interesting to look on from a trader's/ strategy researcher's perspective to make the algorithm more profitable, it would make the scope of the insight we're trying for here more limited. Rather than that, I simply tried looking at recommendations where the most recent target is more than 20% (in absolute value) away from the one before (large changes, corresponding to the top decile of upgrades regarding the change), and small (under 5% changes) that roughly correspond to the bottom decile. The results here are relatively interesting.

Figure 6: Trading only large changes in recommendations (top decile)

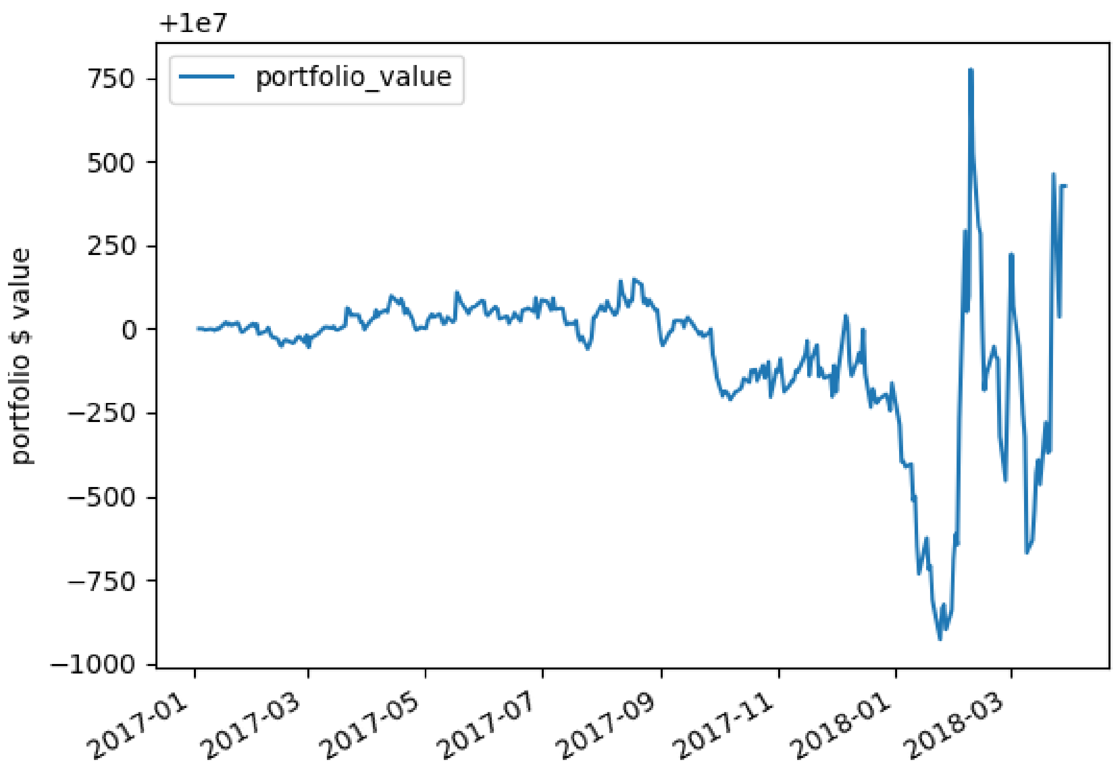
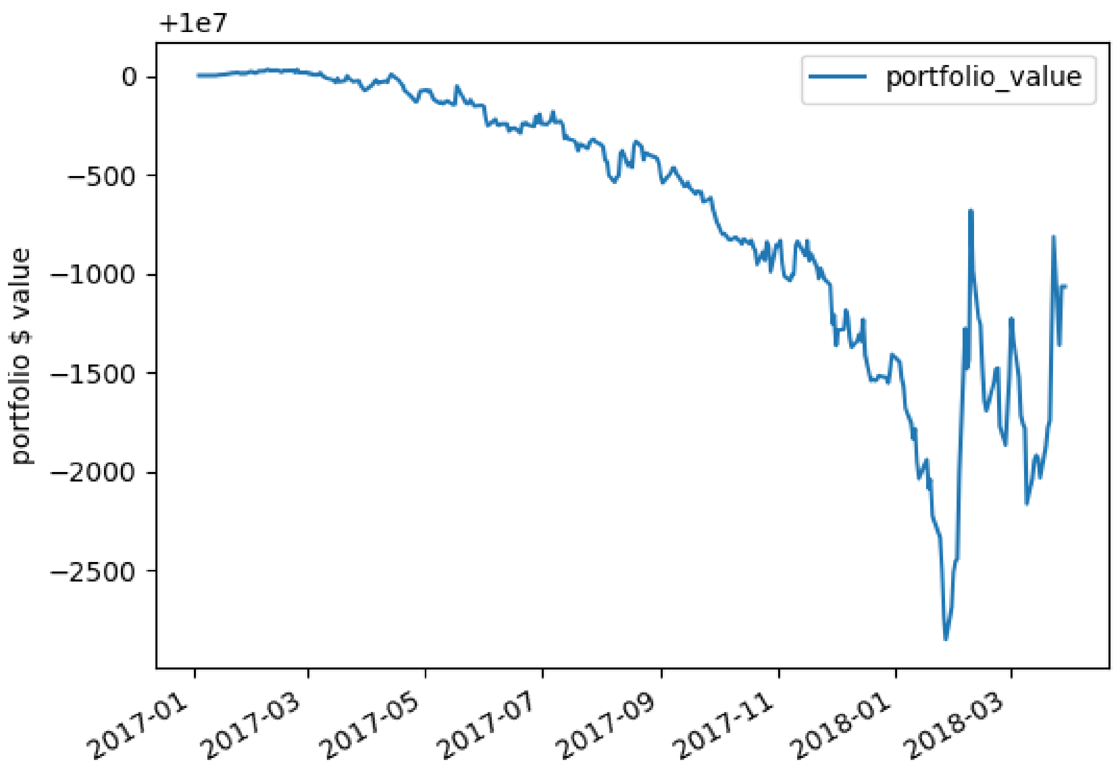


Figure 7: Trading only small changes in recommendations (bottom decile)



While the general trend in realized profits seems similar across the 3 modifications of the strategy, large changes in recommendations seem to have less effect than the small ones. While this is slightly counterintuitive, one explanation that I was able to come up with is that the frequency of updates is likely related to both – reputation of the analyst/institution and the impact the recommendation will have. High reputation recommendations are going to come often, being more precise and reliable, in effect reporting smaller changes in target stock prices. This means that accidentally, we may have found a good proxy for reputation – absolute difference between subsequent target prices.

3.2 Would anyone want an asset with negative returns? – rationale for the market Alpha

This all necessarily leads to one question - is our initial hypothesis false? To answer it, let's first start by answering a seemingly simple question – would anyone ever want to hold an asset with negative (expected) return? A simple answer to that is no, at least not by itself. Let's look at a an example. Take an asset a1, that returns the given profits in three periods, corresponding to vector entries $a1_1$ to $a1_3$. Similarly, there's another asset a2 with different returns.

a1 = [5, 1, -2],

a2 = [-3, 0, 2]

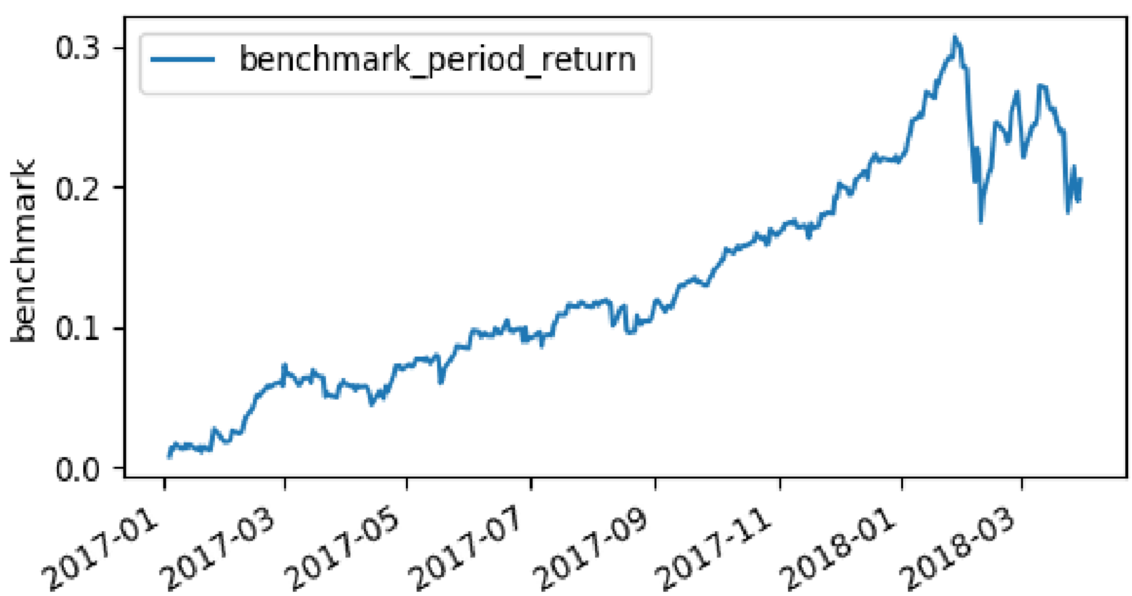
Here, it's not only clear that a1 is the better investment of the two (higher expected return), but also that, taking a very simple approach, no rational person ever invests in a2, since it has an expected return of - 0.33. If we, however combine the two (equally weight them into a portfolio), by simple vector addition, we get:

$$\mathbf{A = a1+a2 = [2, 1, 0]}$$

Which is a risk-free investment – the worst case scenario is that it returns nothing. But its expected return is 1/3 lower than a1. Since we have a riskless investment now, we don't need to worry, borrowing the extra 1/3 of capital and investing into A will yield the same return as a1!

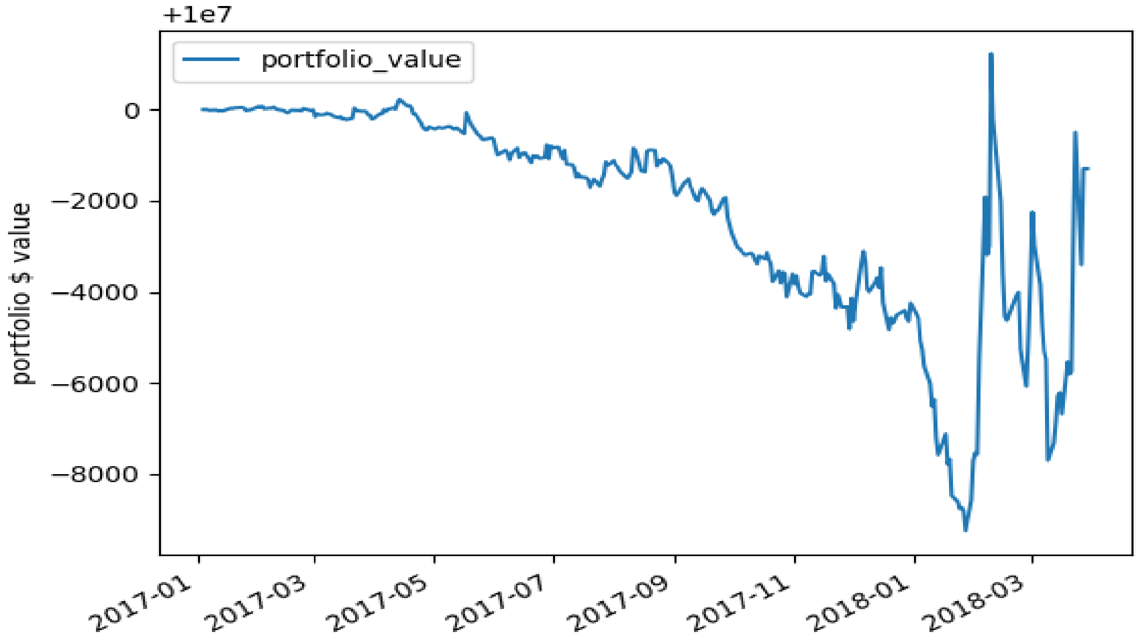
Of course, this is a stylized example. There is usually no such thing as riskless investments and the risk assessment is much more complex than this. But I found it very helpful to understand that assets with negative returns can indeed offer a lot of value when constructing a portfolio. With this in mind, let's look at returns of S&P500, a stock market index, which is often used as a benchmark by asset managers.

Figure 8: Returns of S&P 500 over the period of back testing the strategy



And compare it with the performance of the strategy.

Figure 9: The portfolio performance



Though not perfect, we can see a very strong negative correlation between the two! This hints that our efforts may not have been pointless after all. Furthermore, 61% of our trading ideas were sells, as we're going against recommendations and there's a documented (Womack, 1996) large positive bias for analyst's outlooks. So the negative returns in times of index growth are fully understandable.

The only task that's left is to formalize the extent to which returns of this strategy are of value. One way to approach this is to calculate the alpha – a measure of excess return of a strategy. The idea here is to take a benchmark, usually one of the market indices – S&P500, Russel 3000 (what our dataset consists of), etc. Alpha then measures by how much a strategy outperformed the said benchmark. This makes business sense because it allows us to:

(1) Compare strategies directly
(2) Calculate the excess return of a strategy/asset – how much better or worse have we done in comparison with the market portfolio

Some strategies may be less risky, yielding lower returns and lower risks. The only way of comparing them with the more risky ones is to look at how much return per unit of risk are they generating. Let's start by defining (systematic) risk. A common idea is to approximate it by market Beta B:

$$\mathbf{B_A = Cov(R_A, R_M) / Var(R_M)}$$

, where R_A is the return of an asset (our strategy) and R_M is the return of the market portfolio (Russel 3000 index). The interpretation is rather straightforward – it is a 'multiple' of the market risk. So a Beta of 1.5 means we expect a 1.5 times as big a move in value of our portfolio as is a move in the market (for both directions). CAPM states that return of an asset can be broken down into the risk free rate of return rf, compensation for risk in excess of the risk free rate $R_A - R_F$, proportional to the systematic risk (risk that we can't diversify away like we did with our toy portfolio example earlier) expressed by B.

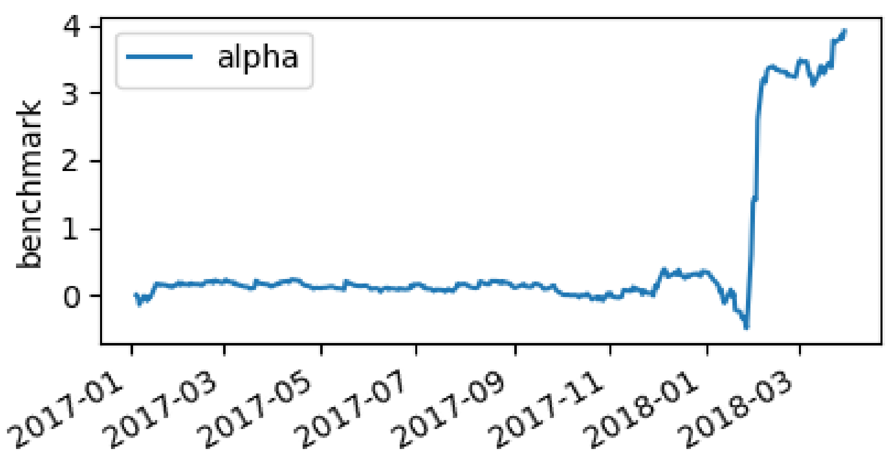
$$\mathbf{R_A = rf + B(R_M - R_F) + Alpha}$$

Anything above these returns is the excess return, i.e. return obtained by taking an advantage of a market inefficiency. Rearranging the above, Alpha simply becomes:

$$\mathbf{Alpha = R_A - Rf - B(R_M - R_F)}$$

Now that we have the tools to calculate the excess returns, let's look at how the strategy did.

Figure 10: Alpha of our strategy



This finally allows us to assess the strategy in a way that doesn't depend on what market returned over the period. We see that, as time progresses and transaction volume increases, so does Alpha. Trading a relatively large number of ideas yields excess returns of somewhere around 3.5- 4 points, something that I consider quite a success given how late (because of the missing time data) the algorithm reacts to the news. Given there's a positive excess return on the strategy and it was generated by over 10 000 transactions, we are now ready to answer the two questions from section 2.2.

Firstly, reacting relatively late to trade the strategy still yields good results. This I consider incredibly surprising, as I hypothesized in the beginning that we'd only observe a very weak effect, and we'd then have to attempt to denoise the return time-series for any kind of insight.

Secondly, the data obtained suggests the presence of the 'second inefficiency'.

4 Discussion, extensions of the work

Testing my ‘second inefficiency’ hypothesis provided two main results. Consistent with the work by Womack (Womack, 1996), I too found positive returns can be achieved by following recommendations of analysts. The other result is an extension of the first one – these returns are a bad deal, since they were achieved in periods of stock market growth and are results of excessive risk-taking. The results, however, may have been different had I been able to obtain time data. But there’s a reason to suspect that the kind of effect we’d be able to confirm would be smaller – there is no reason why the magnitude of this inefficiency would increase as time passes from issue of a recommendation. That being said, it makes sense for the second inefficiency to arise shortly after the release rather than immediately – it might take a retail investor a couple of minutes to interpret the news and execute the corresponding trade.

Lastly, I find it intriguing to think a little about how the work can be extended to test a broader strategy and make the strategy better. Being interested in language and understanding, it’s not awfully difficult for me to sketch a more advanced version of my strategy, that is, unfortunately outside of the scope of this project. One of the approaches to represent words in NLP applications is to have a prediction algorithm such as a neural net transform them into high-dimensional vectors, with each of the entries corresponding to the probability of a particular (always the same) word occurring next to the given word that bis represented by that vector. This means it’s easy to recognize synonyms – choosing an appropriate distance metric of any two or more of these vectors yields a number that proxies word similarity. This framework can be extended to recognize phrases with similar meanings. The reason I mention this here is that we could somehow collect or manually determine phrases that would indicate a positive/negative news about security price outlook and, using the above described principle, trade on actual news automatically, without needing a screening tool such as finviz. Then the data analysis becomes much more interesting, as more insight can be extracted from an entire report than from a numeric summary of it.

4 Conclusion

The following diagram offers a very high-level summarization of the research question and how my work relates to (some of the) important publications that examine it.

Figure 11 : A summary diagram

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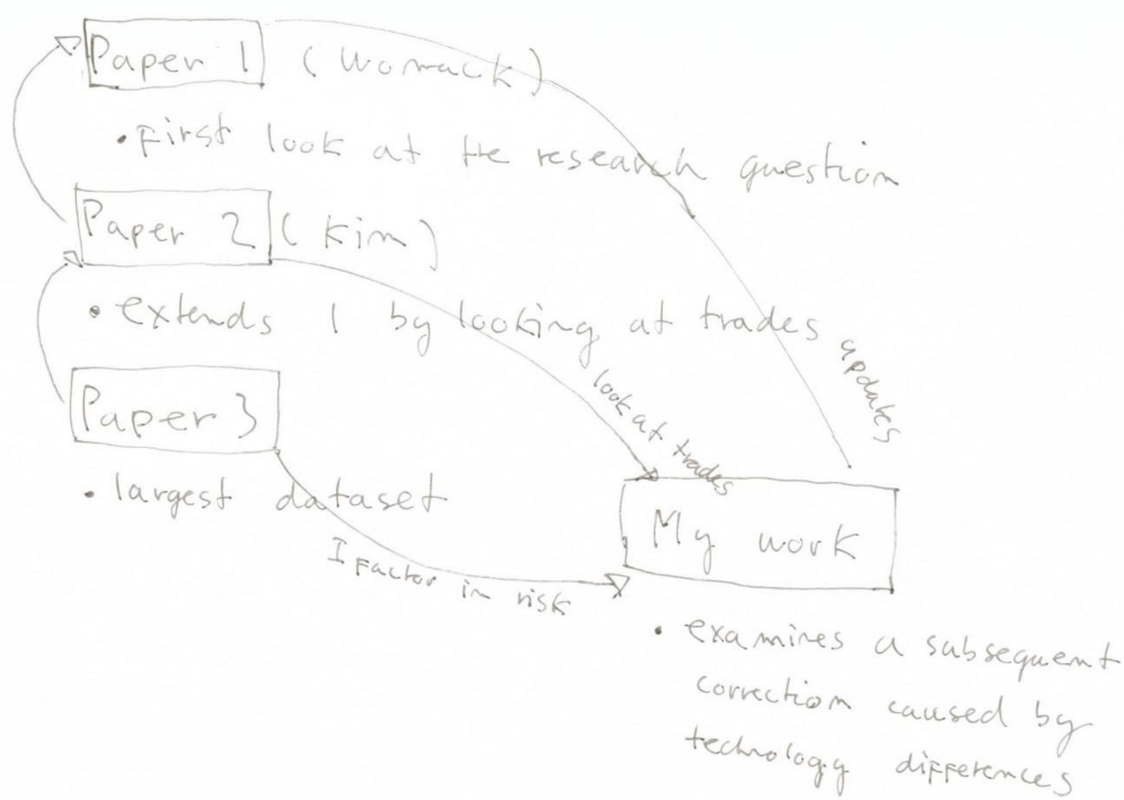

The more narrow question of the relationship between analysts' recommendation and stock prices was first looked in 1996 by Womack, examining whether market prices react to those recommendations (Paper 1). My work can then, in a sense be looked on as updating the results of a 20+ years old paper – qualitatively still observing same effects of recommendations.

Paper 2 (Kim et al) then extended this work by looking at the price effects from investor's perspective – i.e. taking tradability of these effects into account. The reason why this is of high relevance is discussed in the second part of my literature review. My work relates to this paper in that I've designed a trading simulation – rather than looking at price movements as such, I calculated the magnitude of recommendation effects as if we were trading on (against) them.

Paper 3 is the most recent effort (published in 2008) I found to contribute to the research question, having a large dataset to calculate the effects on. I too obtained a relatively large dataset to test the effect, despite calculating the effect as risk-adjusted (abnormal) returns, rather than the kind of absolute returns Paper 3 examines. The reason I prefer this methodologically is further discussed in part 2 of my literature review.

Examining the direct price effect of analysts' recommendations was a byproduct of my analysis, rather than the primary focus. My effort focused on testing the presence of what I refer to as the 'second inefficiency' throughout the paper - I hypothesized there to be a market response to analyst's ratings by the part of participants that are worse informationally and technologically off than high-frequency traders with the capability of taking advantage of the entire inefficiency before them. Going beyond equilibrium price response, it creates an inefficiency in the same direction of the first one (an asset that rises in value after a news release becomes overvalued).

Running a simulation on 12.300 recommendation resulted in me being able to confirm the above hypothesis, with my strategy designed to exploiting it earning a 4 points (percent) of excess/abnormal returns.

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