Do broker/analyst conflicts matter? Detecting evidence from internet trading platforms

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Abstract. We analyze the potential conflict of interest between analysts and brokers associated with each other. In contrast to the existing literature we do not analyze prediction accuracy and/or biases in analyst recommendations. Instead we focus our analysis on brokers and examine whether their behavior systematically differs before and after investment recommendations are released. The evolution and dynamics of brokers' quotes and trades are used to test for systematic trading patterns around the release of one's own investment recommendation. In the model we control for brokers' responses to other investment advice and employ a SUR estimation framework. Data from the Prague Stock Exchange are used to demonstrate our methodology. Finding significant and systematic differences in brokers' behavior, we conclude that misuse of investment recommendations is widespread.

Keywords: dealers' market, emerging markets, informed trading, investment recommendations, trading systems.

JEL Classification: G14, G15, P34
AMS Classification: 62P20, 62J12, 62J05

1 Introduction

The integration of brokerage and analytical services on a stock market creates conditions for a particular type of conflict of interest. This conflict of interest can manifest itself in two ways: First, analysts may have an incentive to issue biased recommendations. Second, even if investment advice is unbiased, associated brokers may possess this information well before the other market participants and use it to their advantage. While the vast majority of theoretical and empirical research on investment recommendations focus on the first issue, i.e., analyst behavior, in this study we explore the second mechanism using publicly available high-frequency data.

We treat the recommendation of a particular analyst as new information that affects the decision-making of all market participants. Associated brokers, however, may have access to this information before it is released to the public and may thus possess an informational advantage over the rest of the market. The primary goal of our paper is to detect the misuse of this advantage by analyzing brokers' trading behavior prior to and after the investment recommendation is issued, with a particular emphasis on their responses to their own recommendations. If there is no conflict of interest, we should not see any **systematic** trading patterns a few trading days before or after an associated analyst issues a recommendation.

Contrary to the existing literature, we don't perform our analysis on restricted-access regulatory data, but use instead publicly available high-frequency data from trading platforms. This way, we do not only introduce a new approach to the analysis of investment recommendations but also overcome the problem of missing data, as the evolution of quotes and trades should very well replace the (often missing) regulatory information on stock inventories, portfolio structure, proprietary trading profits, etc.

1.1 Effect of Investment Recommendations and Emerging Markets

Interestingly, most of the papers analyzing the effects of investment recommendations have been conducted on data from developed capital markets such as that in the U.S., where regulation is quite strict and requires a separation of brokerage and investment banking activities. Therefore, it is not surprising that the results of these studies generally do not support the hypothesis that investors are systematically misled by investment recommendations. It would be a mistake, however, to extend these findings to emerging markets for several reasons, including:

1. Emerging capital markets are typically not subject to a high level of regulation;

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2. Due to the smaller size of emerging markets, brokers have strong market power and substantial latitude for price manipulation;
3. Small investors are inexperienced and unaware of a possible conflict of interest.

In addition, Girard and Biswas [1] show that compared to developed markets, emerging markets exhibit greater sensitivity to the unusual volumes associated with the release of new information such as investment recommendations. Moreover, control over large market participants is usually limited as the regulatory authority often does not collect data on proprietary trading, broker inventories, etc. Overall, the problem of the misuse of investment recommendations and price manipulation could be more severe in emerging markets.

Unfortunately, the existing literature studying the effect of investment recommendations in the context of emerging markets is very limited. Moreover, the existing studies, likely due to the lack of regulatory data, analyze interactions between analyst recommendations and price change. For example, Moshirian, Ng, and Wu [4] in their sample of 13 emerging countries show that stock prices react strongly to stock analyst recommendations. They also report a stronger positive bias in analyst recommendations and revisions in emerging markets compared with that in developed markets. Similarly, Kiymaz [3] analyzed the effects of stock market rumors related to information release at the Istanbul Stock Exchange. He found that positive and significant abnormal returns are observed in the days prior to the publication date and negative yet insignificant returns are observed in the post-publication period. This supports our view of emerging markets, especially the possible existence of information leak and/or strategic trading around the time when recommendations are released.

In this study we use data from the Prague Stock Exchange in the Czech Republic to demonstrate our methodology. The Prague Stock Exchange represents a typical electronic dealers market, in which market makers play a dominant role in affecting the price for a short time interval as well as for a longer period (e.g., Hanousek and Kopriva [2]).

1.2 Methodology – Using Stock Quotes to Analyze Broker Behavior

Our aim is to capture and analyze brokers' trading behavior, particularly focusing on the dates around when associated analysts issue investment recommendations. Recently, several trading platforms enable participants to see real time quotes/positions of each active broker/market maker. So, there exist high-frequency trading data for each broker.

In general, brokers’ trading positions are well described by their buy/sell statistics and by their positions on the bid and ask sides. In our analysis, we omit all cross trades, mainly because of their different nature (for example, some are used to set up standard operations such as the leveraged trading of a broker’s client) and we consider only mandatory trades. For capturing and summarizing a broker’s position on a bid or ask we use the relative distance from the best quotes and average the rank on the bid or ask. Since the original trading data are collected at a high frequency, for daily versions we need to compute the time-weighted averages of these variables.

From the methodological point of view, in our analysis we follow three key steps:

1. Construct statistics that summarize the daily behavior of a given broker from publicly available high-frequency data.
2. Use these statistics as dependent variables in seemingly unrelated regressions (SUR) with information about the timing and direction of investment recommendations used as a regressor.
3. Assess and comment on the differences in trading behavior of brokers before and after their own recommendations as well as the differences in reacting to one’s own as opposed to external recommendations.

In the first step, we summarize brokers’ trading behavior at a daily frequency in the following variables (computed for each share).

a) $Buy_{j,t}$ and $Sell_{j,t}$ = total number of mandatory buys and sells (in lots) by each broker j on trading day t.
b) Time-weighted percentage difference from the best bid (ask), computed for broker j on trading day t.
c) Time-weighted daily average rank on the bid (ask) of broker j.

The variables defined in a) through c) above do not only reflect the trading behavior of a particular broker but also allow for comparison with the behavior of other brokers. We are not only interested in the change of the behavior of an individual broker before and after a particular recommendation is issued, but also in whether his change of behavior is significantly different from the behavior of other brokers on the market.

Since we know the exact timing of each recommendation, we can link them with brokers’ trading behavior and analyze the differences around the releases of the recommendations. The reaction to a particular recommendation differs depending on whether it is a positive (BUY) or negative (SELL) recommendation and also how the particular recommendation compares with his previous recommendation. Therefore, for each broker we define several 0/1 indicators (dummy variables) defining a neighborhood of k trading days before and after the release of the recommendation by associated analysts. The choice of k trading days allows us to see whether there is a reaction and if so how long it lasts (as a baseline we use k = 5 and 10, but we also consider k = 15 and asymmetric windows for robustness checks).

To analyze effect of investment recommendations on the trading behavior of broker j let us consider the following specification:

$$trading_{jt} = \eta_j + \sum_{\substack{r=type\ of \\ reccomendation}} \left[\beta_j \boldsymbol{B}^{r}_{j,own_t} + \alpha_j \boldsymbol{A}^{r}_{j,own_t} + \gamma_j \boldsymbol{B}^{r}_{j,other_t} + \delta_j \boldsymbol{A}^{r}_{j,other_t} + \varphi_j \boldsymbol{B}^{r}_{ext_t} + \phi_j \boldsymbol{A}^{r}_{ext_t}\right] + \varepsilon_j \qquad j=1,\dots,J,\ \ t=1,\dots,D, \tag{1}$$

where the variable $trading$ stands for all trading proxies defined in a) through c), i.e., the number of buys and sells; the percentage difference from the best bid and ask; and the average rank of the bid and ask. As mentioned above, as baselines we will use time windows of five and ten trading days. Here, the dummy variables $\mathbf{B}^{\mathbf{r}}_{\mathbf{j,own}}$, $\mathbf{B}^{\mathbf{r}}_{\mathbf{j,other}}$, and $\mathbf{B}^{\mathbf{r}}_{\mathbf{ext}}$ are equal to one for ten trading days **before** the particular recommendation (own, other and external brokers) has been released. We keep the notation as it is above, where the subscript own is used when the associated analyst posted the recommendation, the subscript other is used when at least one of the other brokers posted the recommendation, and the subscript outside is used when an external analyst posted the recommendation. Similarly, $\mathbf{A}^{\mathbf{r}}_{\mathbf{j,own}}$, $\mathbf{A}^{\mathbf{r}}_{\mathbf{j,other}}$, and $\mathbf{A}^{\mathbf{r}}_{\mathbf{ext}}$ are equal to one for ten trading days **after** the particular recommendation was made public.

As specified in **(1)** we analyze the trading patterns by regressing each particular trading variable on a set of dummies representing the timing of all of the types of recommendation issued by all the kinds of analyst. There exists one potential problem, though. The analysis of trading data could indicate interactions between associated analysts and brokers, but might not detect which came first. If a broker's trading was primarily based on previous knowledge of an associated analyst's recommendation (more likely) or if the recommendation was released in order to maintain the brokers' inventories (less likely), there could be an endogeneity problem related to the timing of the recommendation.

For an estimation of the empirical specification we employ a seemingly unrelated regression (SUR) setup, where for a given share we estimate equations for all brokers $j=1,..,J$ together. This approach provides more efficient estimates of the parameters of interest by using cross-equation correlations caused by, e.g., common exogenous shocks affecting all brokers such as a change in market trends, the common view of the particular stock, etc. Since we estimate specification (1) over the whole sample period, we control for interference between various recommendations (released at a similar time) and the heterogeneous shocks affecting the behavior of all brokers.

2 Data and Descriptive Statistics

For our analysis, we use information about all investment recommendations during the period 2003–2008, which are publicly available online at www.ipoint.cz, together with high frequency data about broker activity on the SPAD trading system of the Prague Stock Exchange (PSE), also publicly available online at www.akcie.cz. In the analysis we only use data on blue chip stocks, i.e., shares from the top-tier trading segment.

The high-frequency trading data consists of all SPAD trades and all SPAD quotes with an identification of brokers/market makers for all stocks traded during the time span 10 February 2004 to 31 December 2008.

Further, we divided the investment recommendations by the type of issuer:

1. investment firms that act also as brokers on the PSE (11 firms),
2. all other external investment analysts/firms who posted at least one investment recommendation during the analyzed time span.

3 Results

The main goal of this study is to find out whether brokers on the stock market misuse the potential informational advantage stemming from their association with analysts. This misuse could manifest in behavior different from other market participants. Even though studying individual patterns of significance and the direction of the coefficients for each stock and broker pair could be interesting from a regulatory point of view, we instead summarize these patterns in a comprehensive way to see the overall picture. During the studied period the Prague Stock Exchange was mostly on an upside trend, so we present here only the results for positive recommendations.

By analyzing the systematic patterns in estimated coefficients, we can answer questions regarding the existence of informational advantage and how it was used.

1. *Are the timing of recommendations unknown to associated brokers?*

This question can be addressed by looking at whether the estimated coefficients $\hat{\beta}_j$ (i.e., a systematic shift before the release of one's own recommendations) are significantly different from zero. For the 10-day window we see significant coefficients in about 28% of the cases for rank positions, 32% of the buy/sell measures, and about 42% of the quotes. For the 5-day window the results are even stronger. We observe significant coefficients in about 30% of the cases for rank positions, 36% of the buy/sell measures and about 44% of the quotes.

2. *Is broker trading behavior (around the time of the investment recommendation) consistent with the recommendation issued by associated brokers?*

Table 1 summarizes the consistent and inconsistent trading behavior of all brokers using a detailed combination of the possible outcomes before and after release of the recommendation.

	Time window	Buy and sell	Bid and ask difference	Bid and ask rank
All 15 companies	5 days	27%	22%	48%
	10 days	28%	27%	21%
Local large companies	5 days	34%	26%	19%
	10 days	30%	32%	29%
Cross-listed companies	5 days	23%	21%	13%
	10 days	33%	27%	15%

Table 1. Broker behavior systematically against his recommendation – sensitivity analysis, across various share groups and trading indicators (positive recommendations, 5- and 10-day windows)

The table contains a simple counting of each broker and stock of trading patterns, which are in line with or against the broker's own recommendation. The summary is based on the significance of the coefficients in specification (1). Below each behavioral proxy we present a ratio of all cases (broker and stock) in which we see the broker's behavior systematically contradicting his recommendations. The group of local large companies consists of O2 , CEZ, UNI, PM, Zentiva, and KB. Cross-listed companies are represented by CME, EB, ORCO and NWR.

From **Table 1** it is clear that the discussed inconsistency between investment recommendations and brokers' trading patterns is not just a coincidence. Very similar results are obtained for both time windows. As the inconsistent combinations indicate a recurring misuse of informational advantage stemming from affiliated analyst recommendations, **Table 1** demonstrates how the broker's behavior systematically contradicts his recommendations across various stock groups and trading proxies.

4 Conclusion

In this study we suggest an innovative approach to testing the potential conflict of interest between analysts and traders, specifically the potential misuse of investment recommendations. In contrast to the main stream of research associated with investment recommendations, we do not analyze the behavior of analysts; neither do we estimate their forecast error nor test if they behave strategically. Instead, we take their investment recommendations as given, including the timing, and analyze the behavior of associated brokers around the time of the release of a recommendation.

The difference in our approach also lies in the use of different data sources. We do not use data from regulating authorities as other studies do. We instead rely on high-frequency data from internet-based trading platforms that allow us to identify the intraday behavior of large brokers (market makers). We define time-weighted variables that summarize a broker's daily trading pattern, including his position on the bid and ask sides.

Our methodological approach is demonstrated on trading data from the Prague Stock Exchange. Results confirm that on this market the above-mentioned conflict of interest exists and is quite severe. Assuming that this result can be generalized to all emerging stock markets, our findings support a need for the regulation of investment recommendations.

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