Understanding rankings of financial analysts

Artur Aiguzhinov (artur.aiguzhinov@inescporto.pt)[1,2], Ana Paula Serra (aserra@fep.up.pt)[1], and Carlos Soares (csoares@fe.up.pt)[2,3]

[1]FEP & CEF.UP, University of Porto

[2]INESC TEC

[3]FEUP, University of Porto

November 24, 2015

Abstract

The prediction of the most accurate analysts is typically modeled in terms of individual analyst characteristics. This approach has its disadvantage that these data are hard to collect and often unreliable. We follow a different approach in which we characterize the general behavior of rankings of analysts based upon state variables rather than individual analyst characteristics or past accuracy. We use a Machine Learning label ranking algorithm that we adapt to model the relation between the selected variables and the rankings. By calculating a ranking-based discriminative power, we show that the uncertainty about future stock performance influences the rankings of the analysts while the macroeconomic variables have the most contribution to the changes in rankings.

1 Introduction

The Efficient Market Hypothesis (EHM) (Fama, 1970) suggests that all public information available to investors is incorporated in prices and new information is immediately reflected in valuations. Yet there are information gathering costs and financial analysts are better than an average investor at processing this information which reflects in issued buy/ sell recommendations. These recommendations, like other news about the general economy as well as about a particular company, influence investors' perception and beliefs.

Previous studies show that analysts stock recommendations have investment value (Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001). The literature also suggests further that foreknowledge of analyst forecast accuracy is valuable (Brown and Mohammad, 2003; Aiguzhinov, Serra, and Soares, 2015). In line with academic research findings, practitioners too pay attention to analyst forecast accuracy rankings. On an annual basis, firms such as The Institutional Investor and StarMine[1] publish analysts ratings according to how well they performed, based partly on past earnings forecast accuracy.

The importance of these ratings should not be ignored because the attention that the market gives to the recommendations of different analysts is expected to correlate with them. Typically, the performance of analysts is analyzed in terms of their individual characteristics (e.g., experience, background) (Clement, 1999). The disadvantage of this approach is that the collection of the necessary data is difficult and it is not always reliable. As for practitioners, they rely mostly on past accuracy to predict future accuracy.

[1] http://www.starmine.com

In this paper we follow an alternative approach. We model the general behavior of rankings of analysts by using variables that characterize the context (state variables) rather than individual analyst characteristics. The model we propose uses the state variables to distinguish which of them affects the rankings the most; hence, influence the analysts' forecast accuracy. In summary, our goal is not to understand relative performance of the analysts in terms of their characteristics but rather in terms of the characteristics of the context in which the analysts operate.

To achieve this goal, we, first, build rankings of analyst based on their EPS forecasts accuracy. Then, we select the state variables that are responsible in differences of analysts' rankings. Finally, we apply a Machine Learning label ranking algorithm to build a model that relates the rankings with the variables and calculates a discriminative power of a variable.

The paper is organized as follows: Section 2 provides the motivation for using rankings of the analysts; Section 3 outlines the state variables that characterize the context; Section 4 outlines the structure of the Machine Learning label ranking model and presents a methodology of building a "variable-ranking" relation; Section 5 describes the datasets used for the experiments; Section 6 summarizes the experiment setup; Section 7 presents and discusses the results; finally, Section 8 concludes this paper.

2 Rankings as a measure of accuracy

In spite of the Efficient Market Hypothesis, it is commonly accepted that the recommendations of financial analysts yield an economic value to investors (Womack, 1996); moreover, recommendations of superior analysts have impact on the market (Loh and Stulz, 2011). For this reason, researchers and practitioners have long been interested in understanding how financial analysts affect capital market efficiency (Ramnath, Rock, and Shane, 2008).

Most researchers conclude that financial analysts are better at making EPS forecasts than mathematical models. Specifically, Fried and Givoly (1982); Bouwman, Frishkoff, and Frishkoff (1987); Brown and Kim (1991) show that analysts are better at forecasting EPS values than any time series models (e.g., ARIMA). The analysts' superiority contributed to the fact that they utilize all available information at and after the date of time series model forecasts. Thus, the context in which analysts make decision matters for their accurate forecast.

In terms of the following advice of the most accurate analysts, it has been shown that the relative accuracy among financial analysts is more important than their absolute accuracy (Aiguzhinov et al., 2015), e.g., in the context of analysts turnover rate (Michaely and Womack, 1999), or in creating value to investors (Aiguzhinov et al., 2015). In addition, financial analysts with superior past accuracy have a greater impact on the market (Park and Stice, 2000). It has also been shown that, under some assumptions, it is safe to assume that analysts with higher forecasting ability produce profitable stock recommendations (Loh and Mian, 2006). This fact is attributed to their deeper research and fundamental accounting knowledge. Furthermore, literature agrees that there is consistency in the superiority of these analysts over time (Li, 2005; Hilary and Hsu, 2013).

Many studies try to correlate the EPS forecasts accuracy of financial analysts with their intrinsic characteristics. However, existing academic research on the behavior of financial analysts have important limitations (Clement, 1999; Brown and Mohammad, 2003; Ramnath et al., 2008), namely an incomplete characterization of the analysts and their recommendations. For instance, Ramnath et al. (2008) address the question of what information affects the recommendations of analysts or how informative are their short-term earnings forecasts, using linear regression on a small sample of data. Despite the promising results, further work is necessary to improve both the methods and the characterization of the context of recommendations.

In this paper, we propose a novel approach in identifying variables that affect the rankings; hence, the relative accuracy of the analysts. The novelty lies in the new methodology of modeling the relationship between the analysts' rankings and the state variables. To build the model, we are required to select the state variables and build analysts rankings.

3 Ranking characterization variables

Several studies try to analyze factors that affect the performance of analysts (Clement, 1999; Brown and Mohammad, 2003; Jegadeesh, Kim, Krische, and Lee, 2004). However, most of these papers look at the individual characteristics of analysts such as their job experience, affiliation, education background, industry specializations. These variables are very important to characterize the relative performance of the analysts in general but they miss the "state-of-the-world" component, i.e., variables that affect all analysts at once. We believe that rankings of analysts capture this component in full.

A ranking is a result of differences in opinion among the analysts concerning the future performance of a company. This implies that there is a variability (dispersion) in analysts' forecasts for a given stock in a given quarter (Diether, Malloy, and Scherbina, 2002). Thus, we can analyze the analysts' forecasts dispersion in terms of its origin and factors that affect it; hence, assuming the same variables affect the rankings. It follows that the variation in rankings is due to the different ability of the analysts to interpret the informational environment (e.g., whether the market is bull or bear). We, thus, select and analyze variables that describe this environment.

To capture the full spectrum of the analyst's decision making process, we select variables based on different levels of information availability: analyst-specific, firm-specific and general economy. In each level, we want a variable to be responsible for information asymmetry and uncertainty. Thus, we believe that these two domains are responsible for the differences in analysts' opinions.

3.1 Analyst-specific variables

On an analyst level, we want to capture the asymmetry of information and uncertainty about the future among the analysts. Particularly, Barron, Stanford, and Yu (2009) point our that the reason for analysts' dispersion is either the uncertainty or the information asymmetry: prior to earnings announcement the uncertainty component prevail, whereas around the time of earnings announcement, information asymmetry is responsible for changes in analysts' opinions.

We use the same set of variables defined in (Barron et al., 2009, page 333):

$$
\begin{aligned}
SE_s &= (ACT_s - \overline{FE_s})^2 \\
disp_s &= \sum_{a=1}^{N} \frac{(FE_{a,s} - \overline{FE_s})^2}{(N-1)} && (1) \\
uncert_s &= \sum_{a=1}^{N} \left(1 - \frac{1}{N}\right) \times disp_s + SE_s && (2) \\
assym_s &= 1 - \frac{SE_s - \frac{disp_s}{N}}{uncert_s} && (3)
\end{aligned}
$$

where SE is the squared error in mean forecast; $\overline{FE}$ is the average per analyst a EPS forecast error (see Section 6.1); and N is the number of analysts in a given quarter for a given stock s.

Equation (1) calculates the dispersion among the analysts which is a variance of EPS forecasts of all analysts for a given stock. Equation (2) defines the uncertainty component of the dispersion per Barron et al. (2009). Equation (3) is the proxy for the information asymmetry.

3.2 Firm-based variables

To be consistent with the two paradigms that characterize the state of the analysts, we split the firm-based variables based on their influence on analysts' opinions. They are either the uncertainty or the information asymmetry.

3.2.1 Uncertainty

The following are the set of the variables and their definitions that we think are responsible for the information uncertainty component.

Business risk. Business risk is associated with the uncertainty in operating results, especially, in operating earnings (Hill and Stone, 1980). An increase in business risk entails an increase in *ex-ante* volatility of the reported earnings (Parkash, Dhaliwal, and Salatka, 1995). We believe that book-to-market ratio can serve as a proxy for the business risk measurement.

$$btm_s = \frac{EQUITY}{MKT.CAP} = \frac{Tot.assts - Tot.liab}{Stocks \times Price} \tag{4}$$

where $Stocks$ is the number of stocks outstanding and $Price$ is the close stock price on last day of a quarter.

Financial risk. Financial risk is responsible for the information uncertainty of the future earnings. More debt implies more variability in earnings as managers would try to maximize the value of a stock using the debt; thus, having high risk of default in the future or taking high risk investment projects. The debt-to-equity ratio is used to capture the financial risk (Parkash et al., 1995). We use short-term debt from the balance sheet (Notes payable) as a measure for debt.

$$dte_s = \frac{DEBT}{EQUITY} = \frac{ShortTermDebt}{Tot.assts - Tot.liab} \tag{5}$$

Size. The firm size can be used as a proxy for amount of information available for a firm. Thus, a larger firm has more news coverage which reduces the uncertainty. An investor is likely to find private information about a larger firm more valuable than the same information about a smaller firm (Bhushan, 1989).

Size is measured as the market value (MV) of the firm as following:

$$size_s = \log(Price \times Stocks) \tag{6}$$

Consistent with the literature, we use log of market value.

Return variability. Return variability influences the uncertainty regarding future earnings (Diether et al., 2002; Henley, Carruth, and Dickerson, 2003). An increase in variability of the abnormal returns is positively correlated with the uncertainty about the earnings; thus, affecting the dispersion among the analysts. To calculate the return variability, we use method outlined in Sousa and Serra (2008), where stock return volatility is decomposed into market and stock specific components as follow:

$$\begin{aligned}
\sigma^2_{mkt} &= \sum_{d \in q} (R_{mkt,d} - \mu_{mkt})^2 \\
\sigma^2_s &= \sum_{d \in q} (R_{s,d} - R_{mkt,d})^2 \\
s.ret_s = Var(R_{s,q}) &= \sigma^2_{mkt} + \sigma^2_s
\end{aligned} \tag{7}$$

where $R_{mkt,q}$ is the market return over sample period; μ_{mkt} is the mean of daily market returns; $R_{s,q}$ is an individual stock return; d is the number of trading days in period q.

3.2.2 Information asymmetry variables

Accruals. Accruals, as a part of earnings, is one of the variables that cause the information asymmetry between managers of a firm and investors. Studies have shown that presence of asymmetry is a necessary condition for the earnings management (Trueman and Titman, 1988; Richardson, 2000). To be more specific, it is the discretionary part of the accruals that causes the information inefficiency in the earnings management (Richardson, 2000; Ahmed, Nainar, and Zhou, 2005). We calculated total accruals-to-total assets ratio defined in Creamer and Stolfo (2009):

$$accr_s = \frac{\Delta C.As - \Delta Cash - (\Delta C.Lb. - \Delta C.Lb.D) - \Delta T - D\&A_q}{(T.As. - T.As._{q-4})/2} \quad (8)$$

where $\Delta X = X_q - X_{q-1}$; $C.As$ – current assets; $C.Lb$ – current liabilities; $C.Lb.D$ – debt in current liabilities; T – deferred taxes; $D\&A$ – depreciation and amortization; and $T.A$ – total assets.

Sector-based variables. The industry specific variables that cause the dispersion in the analysts' forecasts are also connected with the uncertainty concept. One of the variables that is suggested is the variability in the industry Producer Price Index (PPI) (Henley et al., 2003).

$$sec.ret = \sigma(\log PPI_{sec}) \quad (9)$$

where $\sigma(\log PPI_{sec})$ is the standard deviation of the log of SIC sectors' produce price index.

3.3 Macroeconomics variables

In the last set of the state variables, we capture the macroeconomic conditions which affect the analysts' dispersion. For example, different states of the economy are based on different levels of "GNP vs. inflation" combinations (Lev and Thiagarajan, 1993; Hope and Kang, 2005). When economy is booming, i.e. "high GNP-low inflation" state, Lev and Thiagarajan (1993) observe the significant increase in firms' Capital Expenditures coefficient. This implies that firms start enjoy capital investment due to the low cost of capital. This state of the economy produces less uncertainty. In the "medium GNP-high inflation" state of the economy, there is an increase in R&D expenditures, which, from the above mentioned analysis, may spur high level of information asymmetry based on the increase R&D activities. Finally, in the "low GNP-high inflation" state, Lev and Thiagarajan (1993) observe the Doubtful Receivables coefficient is the largest implying that at this recession state many firms go bankrupt or default on the loans – a signal of high uncertainty in the economy. All these states produce the dispersion of the analysts' forecasts.

We select the following set of the macroeconomic variables:

- gnp = Gross National Product;
- $infl$ = Inflation rate;
- $t.bill$ = Interest rate (90-days T-bill rate);
- $vix.ret$ = Market variability (CBOE VIX index)

4 Ranking-based discriminative power

We select the naive Bayes label ranking algorithm (Aiguzhinov, Soares, and Serra, 2010) as a tool to calculate the discriminative power. The basic idea lies in the similarity among rankings conditional on a set of independent variables.

If we define $\mathcal{S}$ as a similarity matrix between the rankings ($\mathcal{S}_{n\times n} = \rho(y_i, y_j)$), then the prior probability of a label ranking is given by:

$$P(y) = \frac{\sum_{i=1}^{n} \rho(y, y_i)}{n} \tag{10}$$

where ρ is the Spearman ranking correlation.

The conditional probability of the value v of attribute x (x_v) given the ranking y is:

$$P(x_v|y) = \frac{\sum_{i:x_i=v} \rho(y, y_i)}{|\{i : x_i = v\}|} \tag{11}$$

We propose that, the discriminative power of x is based on the conditional ranking probabilities of values x and they should: 1) be different from each other; 2) be different from the prior probability. Thus, given the prior ranking $P(y)$ and conditional probability $P(x_v|y)$, the discriminative value of x can be found as follows:

$$DP_x = \frac{1}{n}\sum_{t=1}^{n} \min_{\forall p\neq q} \left\{|P(x_{v_p}|y_t) - P(x_{v_q}|y_t))|\right\} \times \left\{|P(x_{v_p}|y_t) - P(y_t)|\right\} \tag{12}$$

The multiplicand of Equation (12) finds the minimum absolute difference in conditional probabilities between different values of attribute x given ranking y. The multiplier checks that the conditional label ranking probability of x is different from the prior probability of ranking y_t. The case when $DP = 0$ means that x does not discriminate; thus, we consider the cases when $DP > 0$.

We also measure the discriminative variable contribution as a variable's discriminative power share in total discriminative power of all variables:

$$fracDP_x = \frac{DP_x}{\sum_{j=1}^{J} DP_{x=j}} \tag{13}$$

where J is the total number of independent variables.

Panel A of Table 1 shows an example where we have an artificial data for 5 quarters and rankings of 4 equity research firms (A, B, C, D). We assume that we identify some state variables $\{x_1, x_2\}$ that made the rankings as they are in a given quarter. Panel B (C) of the table shows the conditional ranking probabilities of x_1 (x_2).

We apply Equation (12) to calculate a discriminative power of the variable. For an example from Table 1, these values are 0 and 0.007 for variables x_1 and x_2 respectively. Based on this example, we conclude that the most discriminative variable is x_2. The result is intuitive as the variable x_2 takes only two values a and b with value a appearing 4 times; thus, it has more contributive effect on rankings.

5 Data and preliminary results

We selected companies that are publicly traded in either NYSE, NASDAQ, or AMEX. The stocks accounting data was obtained from the Thomson One/Reuters Fundamental database. The analysts[2] EPS forecasts data is from I/B/E/S for each company at study. The descriptive statistics of state variables is presented in Ta-

[2]We use words "analyst" even-though the database is for Equity Research Firms.

ble 2.

We apply a number of requirements for our analysts' data. We select stocks with minimum 12 quarters of coverage by at least one analyst. In addition, for the computational purpose, we require at least 3 analysts per stock in each quarter. We call this a *filtered* set in contrast to *sample* set that includes all analysts and stocks in the sample.

Table 3 outlines the number of stocks, analysts and total forecasts in *sample* (Panel A) and *filtered* datasets (Panel B). For *sample* (*filtered*) data we report 560 (202) unique analysts covering 3517 (1059) stocks during 84 quarters from 1989Q1 until 2009Q4. For this period there were 698291 (164445) issued forecasts.

Table 4 presents the descriptive statistics of *sample* (Panel A) and *filtered* (Panel B) data from the "per analyst" perspective. Concretely, for the *sample* (*filtered*) data the total number of "$Analyst \times Forecasts$" observations is 11796 (7034). Each analyst, on average, issued 59.2 (41.15) forecasts per quarter, and, if we factor in stocks, the average forecasts per stock per quarter becomes 1.35 (1.65). We also report a share of analysts that revise their EPS forecasts within a quarter. For *sample* (*filtered*) data 76.16% (79.09)% of analysts revise their EPS forecasts. Finally, on average, analysts follow stocks for 4.49 (13.71) quarters.

The similar descriptive analysis but from the "per stock" perspective presented in Table 5. Namely, for the *sample* (*filtered*) data the total number of "$Stock \times Forecasts$" observations is 112992 (30073). Each stock, on average, receives 6.18 (9.62) forecasts per quarter. The average forecasts per analyst per quarters is 1.44 (1.67). On average, 61.6% (86.82%) of stocks receive a revision of EPS forecasts within a quarter for *sample* (*filtered*) dataset. Finally, on average, a stock is followed by analysts for 6.76 (14.8) quarters.

Figures on pages 33–35 depict some per quarter statistics. Figure 1 plots log of total number of EPS forecasts for both datasets. We observe that, while both datasets experience a constant growth in issuing forecasts, at the end of the sample period the *filtered* datasets shows a decline which can be contributed to the sub-prime crisis of 2007-2009. When looked at the per quarter forecast statistics in Figure 2, we observe that the analysts in *filtered* dataset issued fewer forecasts per quarter compared to those of the *sample* dataset. Figure 3 plots the average percent of analysts that revise their forecasts (revise from 1 time (top panel) to 5 times (bottom panel) per quarter). We observe that the analysts in *filtered* datasets, on average, are more active in revising their EPS forecasts.

As we observe, despite the smaller number of stocks and total issued forecasts, the *filtered* dataset selects analysts that actively revise their forecasts and has a longer duration of a stock coverage when compared to those of the *sample* dataset. Because of this reason, we use *filtered* dataset to build the rankings.

6 Experiment setup

6.1 Rankings of financial analysts

Analysts are ranked on the basis of Proportional Mean Absolute Forecast Error (PMAFE) that measures the accuracy of a forecast (Clement, 1999; Brown, 2001; Ertimur, Sunder, and Sunder, 2007). First, we define the forecast error $FE_{a,s}$ as an absolute value of the difference between an analyst's a forecasted EPS and actual EPS for each stock s:

$$FE_{a,s} = |ACT_s - PRED_{a,s}| \tag{14}$$

The PMAFE is given as:

$$PMAFE_{a,s} = \frac{FE_{a,s}}{\overline{FE_s}} \tag{15}$$

where ACT_s and $PRED_{a,s}$ are the actual quarterly EPS and analyst a's EPS forecast for stock s respectively.

Second, we rank analysts based on their PMAFE score:

$$rank_{a,s} = \text{rank}_{a=1}^{N} \{PMAFE_{a,s}\} \tag{16}$$

6.1.1 Ranking contingency results

We analyze the analysts' ranking consistency based on the process outlined in Aiguzhinov et al. (2015). Namely, we split the rankings into three terciles (*top*, *medium*, *bottom*). In one particular quarter (t), we place analysts at one of these bins which corresponds to a tercile. We, then, check analysts position at the immediate next quarter ($t+1$) and after one year ($t+4$).

Beforehand, we convert the rankings into scores as follows:

$$score_{a,s} = \frac{rank_{a,s}}{\max rank_s} \tag{17}$$

To get the cross-sectional values of scores across different stocks, we take the average of $score_{a,s}$

$$\overline{score_a} = \frac{1}{k}\sum_{s=1}^{k} score_{a,s} \tag{18}$$

where k is number of stocks followed by a particular analyst a.

Table 6 summarizes the resulted contingency table. We observe that analysts exhibit strong ranking consistency as, on average, they stay at the same tercile. The table demonstrates that 50.05% and 28.83% (46.75% and 30.83%) of the analysts remained in the top and bottom terciles, respectively, after one quarter (year).

6.2 Dynamic states

As we have mentioned above, we want to capture the state of the world in which the analysts operate. For this reason, it is necessary to take into account the dynamics of independent variables from one time period to another. We propose the following methods:

- `static`: no dynamics in the state of the variables, i.e., independent variables used as they are: $x_{\Delta t} = x_t$;
- `diff`: first-difference of the variables, i.e., $x_{\Delta t} = x_t - x_{t-1}$;
- `random`: in time series decomposition of the independent variables, it is an unobserved component: $x_{\Delta t} = T(t) + S(t) + \epsilon(t)$, where $T(t)$- trend, $S(t)$ - seasonal part and $\epsilon(t)$ - random part of time series decomposition.
- `roll.sd`: rolling 8 quarters standard deviation of the independent vari-

ables (Zivot and Wang, 2003):

$$\mu_t(8) = \frac{1}{8}\sum_{j=0}^{7} x_{t-j}$$
$$\sigma_t^2(8) = \frac{1}{7}\sum_{j=0}^{7}(x_{t-j} - \mu(8))^2 \tag{19}$$

Each of these methods produces a different set of attributes. By building a discriminative model on each one of them separately, we get different sets of discriminative power of the variables.

7 Results

We report the result of the discriminative power of the variables in terms of their contribution in affecting the rankings of financial analysts (Equation (13)). Panel A of the Table 7 shows the case of analyst specific variables. We report that *uncert* is the most contributive variable for the all dynamic states with its maximum contribution occurring at the `static` state (14.25%). The least contributive variable of the analysts specific variables is the *assym*, the asymmetry of information, with the smallest share of contribution to the discriminative power (2.23%, 1.73%, 1.62%, 0.16% for the `static`, `diff`, `random`, and `roll.sd` states respectively). Thus, our model of the discriminative power suggests that in the `static` state, of all analysts' specific variables, the rankings are most affected by the earnings uncertainty.

Panel B of Table 7 presents the contribution of stock specific variables. We report that in each of the dynamic states the *s.ret* (*size*) showed the maximum (minimum) contribution to the difference in analysts' opinions regarding EPS forecasts (8.68% (0.23%), 9.39% (0.4%), 13.66% (0.76%), 12.76% (1.3%) for the `static`, `diff`, `random`, and `roll.sd` states respectively). As we defined above, the variability of stock returns is the measure of uncertainty about future earnings; thus, we report that, similar to the analyst-specific variables, the uncertainty is responsible for the rankings when consider stock-specific variables.

Finally, panel C shows the case of macroeconomic variables. Contrary to the previous variable types, the distribution of the most contributive individual variable differs across different states. For the `static` state, it is *infl* (27.59%) whereas for the all others states it is *t.bill* (25.69%, 21.98%, 26.02% for the `diff`, `random`, and `roll.sd` states respectively). The least contributive variable is the *vix.ret*: 0.38%, 0.45%, 1.64%, and 0.92% for the `diff`, `random`, and `roll.sd` states respectively.

The cross panel analysis of Table 7 show that the macroeconomic variables are the most contributive of all. Specifically, the `roll.sd` state accounts for 73.56% of total contribution in differences in rankings; for other states the share of these variables are (in a decreasing order) 61.32%, 59.98%, and 58.32% for the `diff`, `static`, and `random` states respectively. Figure 4 depicts the plot of total contribution of each of the variable conditional on variable types. Thus, we conclude that the condition of the economy represented by the GNP, inflation rate, stock market volatility, and interest rate is the one that influence the most analysts' opinions about future stocks' performance with respect to their earnings.

We also perform a hypothesis pairwise test of whether the discriminative power of variables in the dynamic states is significantly different from those in the `static` state. We report results in Table 8. Panel A shows significance of analysts specific variables in dynamic states. We reject the *null* hypothesis at 1% significance level in all variables of this category for the states `diff` and `random`, and variables *uncert* and *assym* for the `roll.sd` state. We fail to reject the *null* for the variable *disp* for the `roll.sd` state at 10% significance. Panel B presents the case of stock-specific variables and we report that we reject the *null* for all variables for all dynamic states except *accr* for the `roll.sd` state. Finally, panel C shows the case of macroeconomic variables and we also reject the *null* for all the variables and states except *infl* in the `diff` state.

Figure 5 plots the percentage split of the average *DP* between the analyst-, stock-specific, and macroeconomic variables per quarter for each of the states. We observe that, as mentioned above, macroeconomic variables are the most contributive components to the analysts' rankings. In the `diff` state, it is visible that at the end of the sample period (years 2006–2009) analyst-specific variables become more contributive.

8 Conclusion

Some institutions, such as StarMine, rank financial analysts based on their accuracy and investment value performance. These rankings are published and are relevant: stocks favored by top-ranked analysts will probably receive more attention from investors. Therefore, there is a growing interest in understanding the relative performance of analysts. Typical approaches are based on individual characteristics of those analysts or past analyst forecasting accuracy. Here, we follow an alternative approach that links the general behavior of rankings of analysts to variables that explain the uncertainty and information asymmetry on analyst-specific, stock-specific, and macroeconomic levels.

We introduce a new approach, based on the naive Bayes Label Ranking algorithm, in identifying the discriminative power of a variable; thus, its contribution to the rankings conditional on different states of the world: static state, first-difference, random part of time-series decomposition, and sliding standard deviation.

We report that for the analysts- and stock-specific variables, the uncertainty about future stock performance is the most contributive to the changes in rankings. The macroeconomic variables influence rankings the most considering all variables at once.

For the future work we would like to take the findings of this paper and apply them to the problem of predicting the actual rankings of the analysts.

References

Ahmed, A., S. Nainar, and J. Zhou (2005). Do analysts' earnings forecasts fully reflect the information in accruals? *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration 22*(4), 329–342.

Aiguzhinov, A., A. Serra, and C. Soares (2015). Are rankings of financial analysts useful for investors? http://ssrn.com/abstract=2680094. Last checked on 26/10/2015.

Aiguzhinov, A., C. Soares, and A. Serra (2010). A similarity-based adaptation of naive Bayes for label ranking: Application to the metalearning problem of algorithm recommendation. In B. Pfahringer, G. Holmes, and A. Hoffmann (Eds.), *Discovery Science*, Volume 6332 of *Lecture Notes in Computer Science*, pp. 16–26. Springer Berlin Heidelberg.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman (2001). Can investors profit from the prophets? Security analyst recommendations and stock returns. *The Journal of Finance 56*(2), 531–563.

Barron, O., M. Stanford, and Y. Yu (2009). Further evidence on the relation between analysts' forecast dispersion and stock returns. *Contemporary Accounting Research 26*(2), 329–357.

Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics 11*(2-3), 255–274.

Bouwman, M., P. Frishkoff, and P. Frishkoff (1987). How do financial analysts make decisions? A process model of the investment screening decision. *Accounting, Organizations and Society 12*(1), 1–29.

Brown, L. (2001). How important is past analyst earnings forecast accuracy? *Financial Analysts Journal 57*(6), 44–49.

Brown, L. and K. Kim (1991). Timely aggregate analyst forecasts as better proxies for market earnings expectations. *Journal of Accounting Research 29*(2), 382–385.

Brown, L. and E. Mohammad (2003). The predictive value of analyst characteristics. *Journal of Accounting, Auditing and Finance 18*(4), 625–647.

Clement, M. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics 27*(3), 285–303.

Creamer, G. and S. Stolfo (2009). A link mining algorithm for earnings forecast and trading. *Data Mining and Knowledge Discovery 18*(3), 419–445.

Diether, K., C. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance 57*(5), 2113–2141.

Ertimur, Y., J. Sunder, and S. Sunder (2007). Measure for measure: The relation between forecast accuracy and recommendation profitability of analysts. *Journal of Accounting Research 45*(3), 567–606.

Fama, E. (1970). Efficient capital markets: A review of empirical work. *The Journal of Finance 25*, 383–417.

Fried, D. and D. Givoly (1982, Jan). Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting and Economics 4*(2), 85–107.

Henley, A., A. Carruth, and A. Dickerson (2003). Industry-wide versus firm-specific uncertainty and investment: British company panel data evidence. *Economics Letters 78*(1), 87–92.

Hilary, G. and C. Hsu (2013). Analyst forecast consistency. *The Journal of Finance 68*(1), 271–297.

Hill, N. and B. Stone (1980). Accounting betas, systematic operating risk, and financial leverage: A risk-composition approach to the determinants of systematic risk. *Journal of Financial and Quantitative Analysis 15*(03), 595–637.

Hope, O. and T. Kang (2005). The association between macroeconomic uncertainty and analysts' forecast accuracy. *Journal of International Accounting Research 4*(1), 23–38.

Jegadeesh, N., J. Kim, S. Krische, and C. Lee (2004). Analyzing the analysts: When do recommendations add value? *The Journal of Finance 59*(3), 1083–1124.

Lev, B. and S. Thiagarajan (1993). Fundamental information analysis. *Journal of Accounting research 31*(2), 190–215.

Li, X. (2005). The persistence of relative performance in stock recommendations of sell-side financial analysts. *Journal of Accounting and Economics 40*(1), 129–152.

Loh, R. and G. Mian (2006). Do accurate earnings forecasts facilitate superior investment recommendations? *Journal of Financial Economics 80*(2), 455–483.

Loh, R. and R. Stulz (2011). When are analyst recommendation changes influential? *Review of Financial Studies 24*(2), 593–627.

Michaely, R. and K. Womack (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies 12*(4), 653–686.

Park, C. and E. Stice (2000). Analyst forecasting ability and the stock price reaction to forecast revisions. *Review of Accounting Studies 5*(3), 259–272.

Parkash, M., D. Dhaliwal, and W. Salatka (1995). How certain firm-specific characteristics affect the accuracy and dispersion of analysts' forecasts:: A latent variables approach. *Journal of Business Research 34*(3), 161–169.

Ramnath, S., S. Rock, and P. Shane (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting 24*(1), 34–75.

Richardson, V. J. (2000). Information asymmetry and earnings management: Some evidence. *Review of Quantitative Finance and Accounting 15*(4), 325–347.

Sousa, S. and A. Serra (2008). What drives idiosyncratic volatility over time? *Portuguese Economic Journal 7*(3), 155–181.

Trueman, B. and S. Titman (1988). An explanation for accounting income smoothing. *Journal of Accounting Research 26*, 127–139.

Womack, K. (1996, March). Do brokerage analysts' recommendations have investment value? *The Journal of Finance 51*(1), 137–168.

Zivot, E. and J. Wang (2003). *Modeling financial time series with S-PLUS*, Volume 191. Springer Berlin Heidelberg.

Table 1: Example of Label Ranking problem

The table presents an example of label ranking problem (Panel A). Panel B (panel C) shows the conditional label ranking probabilities for variable x_1 (x_2) obtained from Equation (11)

Panel A: Example of LR ranking problem

t	x_1	x_2	Ranks			
			A	B	C	D
1	a	b	1	2	3	4
2	b	a	2	1	3	4
3	c	a	3	2	1	4
4	d	a	4	3	2	1
5	e	a	4	1	2	3

Panel B: conditional LR probability o f x_1

	a	b	c	d	e	priors
1	0.34	0.31	0.21	0.00	0.14	0.58
2	0.26	0.29	0.21	0.03	0.21	0.68
3	0.17	0.20	0.29	0.11	0.23	0.70
4	0.00	0.05	0.19	0.48	0.29	0.42
5	0.11	0.20	0.23	0.17	0.29	0.70

Panel C: conditional LR probability of x_2

	b	a	a	a	a	priors
1	0.31	0.34	0.34	0.34	0.34	0.58
2	0.29	0.26	0.26	0.26	0.26	0.68
3	0.20	0.17	0.17	0.17	0.17	0.70
4	0.05	0.00	0.00	0.00	0.00	0.42
5	0.20	0.11	0.11	0.11	0.11	0.70

Table 2: Descriptive statistics of independent variable

The table presents the descriptive statistics of state variables that influence the ranking of the analysts.

Type	Variable	Stock	Median	Mean	std.dev	ACF (lag=1)
Analyst	uncert	988	0.001	0.629	10.881	0.983
	assym	988	0.155	0.403	0.484	0.978
	disp	988	0.000	0.006	0.125	0.971
Stock	btm	981	0.404	35.263	481.567	0.985
	size	981	20.856	20.795	1.577	0.978
	dte	608	0.004	0.131	0.651	0.984
	accr	960	-0.012	1.981	67.357	0.973
	s.ret	988	0.029	0.054	0.081	0.975
	sec.ret	988	0.021	0.008	0.119	0.977
Macro	gnp	988	0.014	0.013	0.005	0.975
	infl	988	0.007	0.008	0.005	0.975
	vix.ret	988	-0.049	0.013	0.309	0.980
	t.bill	988	0.049	0.048	0.023	0.979

Table 3: Summary of *sample* and *filtered* data

The table presents the total number of stocks, analysts and EPS forecasts for *sample* (Panel A) and *filtered* (Panel B) data.

Sector	# stocks	# analysts	# forecasts
Panel A: *sample* data			
Consumer Discretionary	567	336	144 754
Consumer Staples	155	215	28 593
Energy	277	205	88 289
Financials	650	228	93 656
Health Care	526	309	76 680
IT	697	413	159 012
Industrials	464	320	80 331
Materials	64	163	12 119
Telecom Services	14	93	1 882
Utilities	103	120	12 975
Total	3 517	560	698 291
Panel B: *filtered* data			
Consumer Discretionary	214	124	34 199
Consumer Staples	42	61	7 155
Energy	99	63	24 819
Financials	178	76	24 606
Health Care	118	91	16 791
IT	221	123	34 590
Industrials	146	101	17 900
Materials	25	46	3 183
Telecom Services	4	14	328
Utilities	12	18	874
Total	1 059	202	164 445

Table 4: Descriptive statistics of forecasts per analyst

The table presents the descriptive statistics for *sample* (Panel A) and *filtered* (Panel B) data. Namely, the table shows the total number of analyst-forecast observations, the average number of forecast per quarter, the average number of following stocks per analyst, the average number of forecasts per stock per analyst, share of analysts that make forecast revisions, and, finally, the average number of quarters a analyst follows a stock.

	Obsrv	Frcst/q	Stocks	Frcst/stock	Rev.	follow time, q
Panel A: *sample* data						
Consumer Discretionary	7 405	19.55	11.65	1.40	0.72	5.06
Consumer Staples	3 797	7.53	4.81	1.36	0.60	5.29
Energy	3 541	24.93	12.68	1.50	0.71	5.74
Financials	4 506	20.78	13.00	1.38	0.66	5.52
Health Care	5 812	13.19	8.87	1.29	0.63	4.14
IT	8 018	19.83	12.89	1.34	0.69	4.67
Industrials	6 290	12.77	8.47	1.32	0.65	5.04
Materials	2 531	4.79	3.00	1.44	0.56	6.26
Telecom Services	821	2.29	1.70	1.28	0.39	4.85
Utilities	1 662	7.81	5.53	1.27	0.52	4.34
Total	11 796	59.20	36.83	1.35	0.76	4.49
Panel B: *filtered* data						
Consumer Discretionary	3 966	15.81	8.62	1.70	0.76	13.71
Consumer Staples	1 967	6.07	3.64	1.58	0.65	13.90
Energy	2 212	23.78	11.22	1.96	0.80	17.84
Financials	2 719	15.66	9.05	1.66	0.70	15.19
Health Care	2 708	10.08	6.20	1.49	0.67	13.13
IT	4 007	14.13	8.63	1.56	0.74	13.62
Industrials	3 036	9.36	5.90	1.55	0.70	12.90
Materials	1 230	4.39	2.59	1.71	0.62	13.45
Telecom Services	236	1.89	1.39	1.40	0.40	11.93
Utilities	421	3.46	2.08	1.64	0.58	12.30
Total	7 034	41.15	23.38	1.65	0.79	13.71

Table 5: Descriptive statistics of forecasts per stock

The table presents the descriptive statistics per stock for *sample* (Panel A) and *filtered* (Panel B) data. Namely, the table shows the total number of stock-forecast observations, the average number of forecast per quarter per stock, the average number of following analysts per stock, the average number of forecasts per analyst per stock, share of stocks that got their forecast revised by analysts ,and, finally, the average number of quarters a stock being followed by a analyst.

	Obsrv	Frcst/q	analysts	Frcst/analyst	Rev.	follow time, q
Panel A: *sample* data						
Consumer Discretionary	20 772	6.97	4.15	1.47	0.66	7.19
Consumer Staples	5 321	5.37	3.43	1.42	0.63	6.56
Energy	8 325	10.61	5.39	1.67	0.76	7.62
Financials	17 222	5.44	3.40	1.49	0.58	7.20
Health Care	14 407	5.32	3.58	1.33	0.57	5.45
IT	22 469	7.08	4.60	1.40	0.64	6.63
Industrials	17 187	4.67	3.10	1.41	0.59	7.09
Materials	2 518	4.81	3.02	1.44	0.62	7.28
Telecom Services	399	4.72	3.51	1.33	0.56	5.41
Utilities	4 372	2.97	2.10	1.27	0.42	5.69
Total	112 992	6.18	3.84	1.44	0.62	6.76
Panel B: *filtered* data						
Consumer Discretionary	6 254	10.03	5.47	1.74	0.89	15.08
Consumer Staples	1 499	7.96	4.77	1.64	0.86	15.03
Energy	3 432	15.33	7.23	2.01	0.94	18.80
Financials	4 782	8.90	5.15	1.65	0.86	14.91
Health Care	3 235	8.44	5.19	1.58	0.84	13.95
IT	5 780	9.79	5.98	1.59	0.87	13.75
Industrials	4 017	7.08	4.46	1.57	0.83	14.23
Materials	760	7.10	4.19	1.65	0.85	14.47
Telecom Services	80	5.59	4.10	1.35	0.72	11.50
Utilities	234	6.23	3.74	1.65	0.82	11.08
Total	30 073	9.62	5.47	1.67	0.87	14.80

Table 6: Analysts' rankings contingency

The contingency table shows changes in analysts' *top*, *middle*, *bottom* ranking bins. Panel A (B) is the results of the rankings based on the *sample* (*filtered*) dataset.

		top	$middle$	$bottom$	Sum
			$t+1$		
	top	50.1	25.5	25.2	100.8
	$middle$	49.8	25.7	25.5	101.1
	$bottom$	46.0	26.3	28.8	101.1
t			$t+4$		
	top	46.8	28.4	27.0	100.8
	$middle$	46.0	27.7	28.3	101.1
	$bottom$	44.8	27.7	30.8	101.1

Table 7: Contribution of each of the variable to rankings, in %

The table shows the percent of contribution of the variable's *DP* value to total value of *DP*. State `static` is the state with no dynamics in values of the variables, `diff` is the state with first-difference in values, `random` is the state that captures the random part of values time-series decomposition, and `roll.sd` is the state of variable sliding 8 quarters standard deviation.

Variable	`static`	`diff`	`random`	`roll.sd`
Panel A: Analyst				
uncert	14.25	12.49	9.71	1.25
assym	2.23	1.73	1.62	0.16
disp	9.00	8.81	4.79	0.67
Total	25.47	23.03	16.11	2.08
Panel B: Stock				
btm	0.78	1.91	3.04	3.37
size	0.23	0.40	0.76	1.30
dte	1.68	2.52	2.83	4.05
accr	1.74	0.77	1.96	1.31
s.ret	8.68	9.39	13.66	12.76
sec.ret	1.43	0.66	3.31	1.57
Total	14.54	15.65	25.57	24.37
Panel C: Macro				
gnp	22.03	17.53	18.12	24.26
infl	27.59	17.65	16.58	22.37
vix.ret	0.38	0.45	1.64	0.92
t.bill	9.99	25.69	21.98	26.02
Total	59.98	61.32	58.32	73.56

Table 8: Significance of dynamic states

This table shows the results of pairwise t-test of `static` state of the variables vs. the dynamic states. The null is that the difference in *DP* values is zero. State `static` is the state with no dynamics in values of the variables, `diff` is the state with first-difference in values, `random` is the state that captures the random part of values time-series decomposition, and `roll.sd` is the state of values sliding 8 quarters standard deviation.

Variable	`diff`		`random`		`roll.sd`	
	t value	Pr($>\|t\|$)	t value	Pr($>\|t\|$)	t value	Pr($>\|t\|$)
Panel A: Analyst						
uncert	9.31	0.00	15.88	0.00	7.61	0.00
assym	5.57	0.00	8.24	0.00	3.46	0.00
disp	2.53	0.01	9.74	0.00	1.61	0.11
Panel B: Stock						
btm	8.70	0.00	13.04	0.00	12.78	0.00
size	4.32	0.00	5.91	0.00	8.57	0.00
dte	8.61	0.00	6.80	0.00	4.61	0.00
accr	-3.16	0.00	3.63	0.00	-0.73	0.47
s.ret	11.46	0.00	22.24	0.00	17.68	0.00
sec.ret	-4.15	0.00	8.62	0.00	1.90	0.06
Panel C: Macro						
gnp	9.35	0.00	31.81	0.00	24.94	0.00
infl	-0.67	0.50	26.21	0.00	19.35	0.00
vix.ret	1.63	0.10	7.23	0.00	4.17	0.00
t.bill	40.58	0.00	29.88	0.00	43.02	0.00

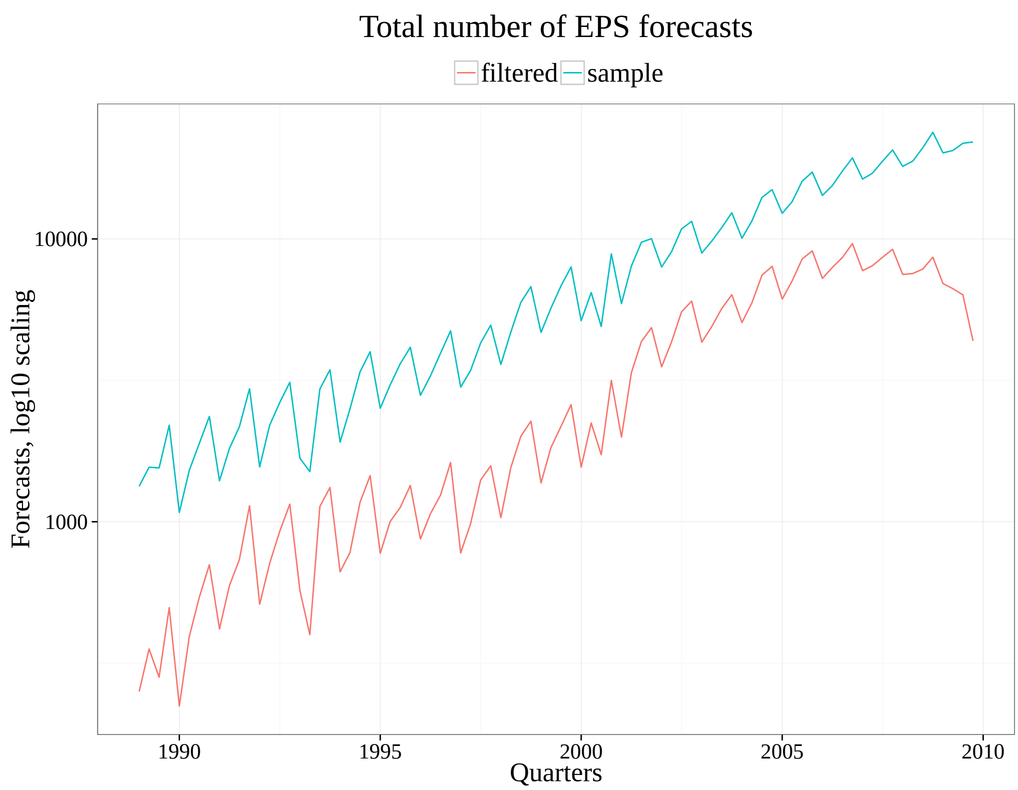

Figure 1: Total number of EPS forecasts.

The plot shows the log of total number of forecasts per quarter for *sample*d and *filtered* data sets.

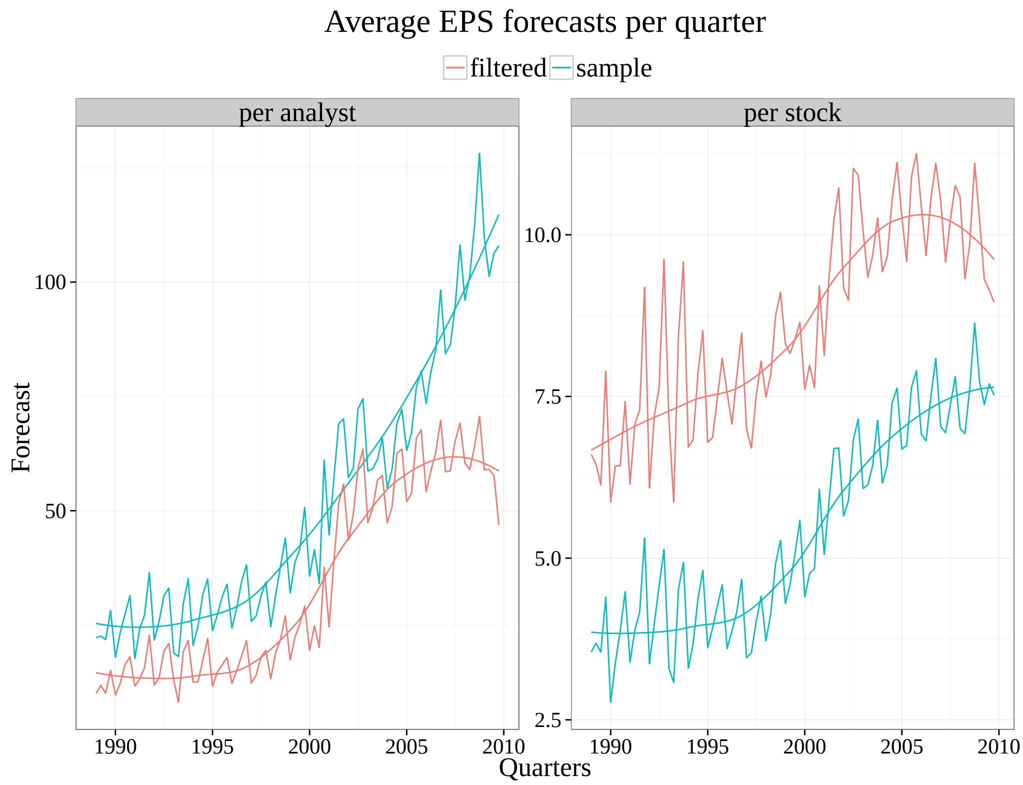

Figure 2: Average number of EPS forecasts

The plot depicts the average number of EPS forecasts per analyst (left panel) and per stock (right panel) for *sample* and *filtered* datasets.

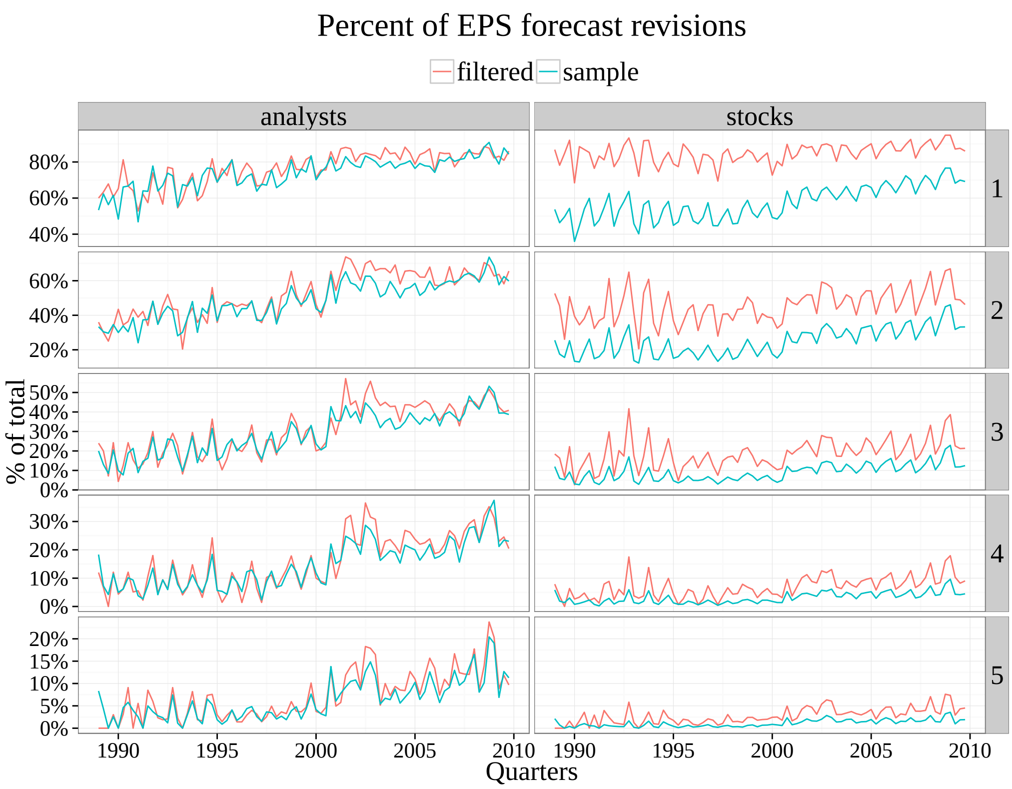

Figure 3: Revisions of forecasts

The plot shows the average percent of analysts (stocks) that revise (got revised) their forecasts for *sample* and *filtered* dataset. Horizontal panels shows the number of revisions per quarter from 1 revision per quarter (top panel) to 5 (bottom panel).

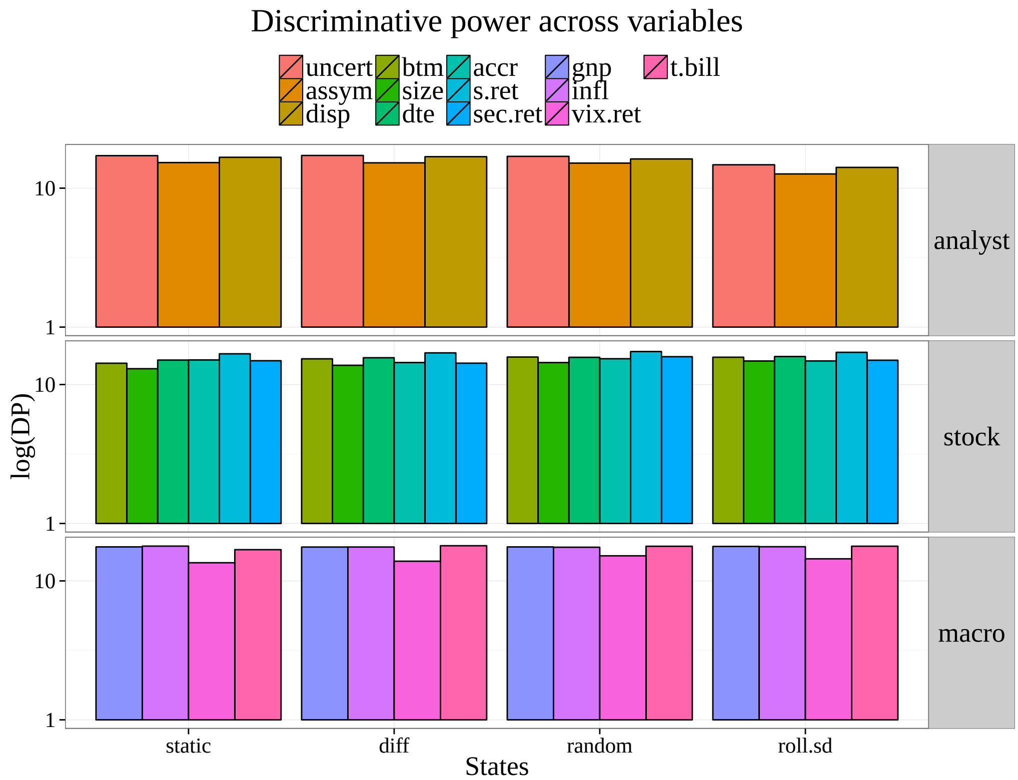

Figure 4: The discriminative power of the variables.

The plot depicts the discriminative power of variables. State `static` is the state with no dynamics in values of the variables, `diff` is the state with first-difference in values, `random` is the state that captures the random part of values time-series decomposition, and `roll.sd` is the state of variable sliding 8 quarters standard deviation.

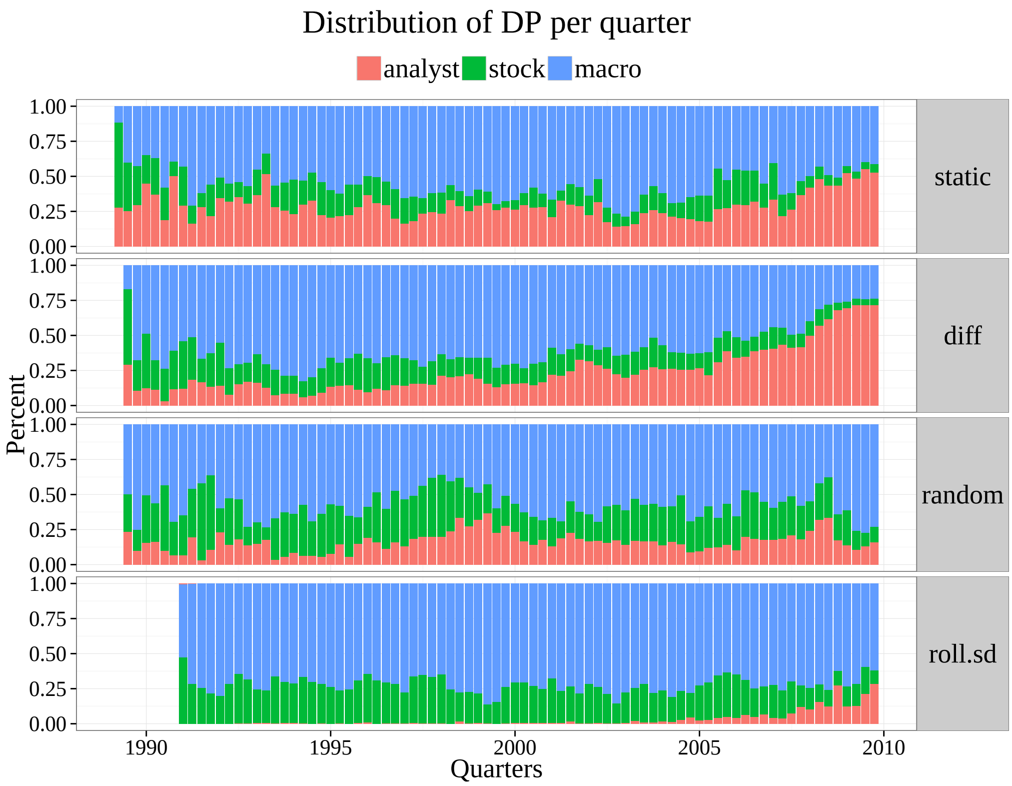

Figure 5: Distribution of discriminative power per quarter

The plot shows the composition of discriminative power across variable categories. The states are: `static` is the state with no dynamics in values of the variables, `diff` is the state with first-difference in values, `random` is the state that captures the random part of values time-series decomposition, and `roll.sd` is the state of variable sliding 8 quarters standard deviation.