

The Information Content of Analyst Forecasts—  
An Econometric Analysis of Informational Leadership

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## Abstract

We measure the information content of monthly analyst consensus forecasts for one-year-forward earnings per share (EPS) based on two well-established price discovery measures drawn from the area of market micro-structure research. Employing a 36-year sample of large American companies listed in the S&P 100 Index, we compute (i) Hasbrouck's information shares and (ii) Gonzalo and Granger's common factor components to measure the relative share that the capital market and the analysts have in the process of price discovery. We find that while analysts do not lead the capital market, they have a small but significant share in the process of price discovery, amounting to 4.5% (Hasbrouck) or 18.0% (Gonzalo and Granger) on average. This share varies significantly in the cross-section. We identify a company's analyst coverage as an explanatory factor: The larger the coverage, the lower is the analysts' information share. This finding can be explained by analysts' herding behavior, which lowers the information content of their estimates.

JEL Classification: G12, G14, G17, G2, C32, C53, D82

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# 1 Introduction

On capital markets, financial analysts act as information intermediaries. Ideally combining strong economic knowledge and a close connection to the management of the companies on their coverage list, their key tasks are the estimation of the companies' prospects and their transformation into earnings forecasts, target prices, buy-sell-hold recommendations etc. Based on economic foundations, analysts are challenged to increase informational market efficiency, which means speeding up the process of price discovery and reducing conflicts induced by agency issues.

However, the notion that analysts lead capital markets and increase the speed of price discovery conflicts with the theory of informationally efficient markets. According to the efficient market hypothesis (EMH), stock prices always fully reflect all available information relevant to investors. Therefore, on informationally efficient markets, financial analysts are no longer important information intermediaries, since every single information relevant to investors is already incorporated in the stock price.

The empirical question as to what degree analysts are able to fulfill their role and whether analyst output does at all contain information which is relevant to the market remains open and is still vigorously discussed in the empirical literature. Most publications in this area apply event studies in order to identify and measure abnormal stock returns coinciding with the release of new analyst content. Another extensive strand of literature formulates trading strategies which aim at generating abnormal returns by exploiting earnings forecast momentum effects.

In this paper, we propose a completely different method for analyzing the informational contribution of financial analysts: Adapting econometric approaches from market microstructure theory, we measure the contribution of analysts to the discovery process for the price of a stock. By means of this method, we can not only answer the questions of whether analyst forecasts lead stock prices or prices lead forecasts, but can quantify the extent to which such a lead-lag relationship exists. To the best of our knowledge, this is the first paper that directly measures the percentage share of price discovery between stock prices and analyst forecasts, thus providing a quantitative measure for the information content of the analysts.

We measure the information content of monthly analyst consensus forecasts of earnings per share (EPS) as the central analyst output. According to Hax (1998), earnings forecasts are the analysts' key estimates from which further output such as target prices, buy-sell-hold recommendations, etc. are derived. Assuming a simple relationship between future EPS and stock value (in the spirit of the Gordon (1959) model), changes in EPS estimates induce changes in the analysts' view of the stock value. Stock prices and such forecast-based implied stock prices should co-integrate and therefore share a common stochastic component. Based on a vector error correction model (VECM) and a 36-year sample of large US companies listed in the S&P 100 Index, we compute Hasbrouck (1995) information shares and Gonzalo and Granger (1995) common factor components as measures for the share of information contribution.

Our findings show that financial analysts significantly participate in the process of price discovery: On average, they aggregate a percentage share of 4.5% (Hasbrouck measure) or even 18.0% (Gonzalo and Granger measure), respectively. These figures vary considerably

in the cross-section, ranging from 0 to 33.3% (Hasbrouck) or 0 to 59.3% (Gonzalo and Granger).

We find that a company's mean level of analyst coverage has a significant negative effect on the analysts' information share. This finding can be explained by a herding argument: Individual analysts may shrink from opposing a strong consensus forecast based on a large number of individual estimates. Consequently, herding behavior causes EPS forecasts to be more biased and thus less informative in the case of high coverage. Compared to consensus EPS forecasts that are made up of only a small number of estimates, high-coverage forecasts are thus less informative.

The remainder of this article is organized as follows. In Section 2, we present the theoretical foundations and a literature review. The econometrical framework and methodological approach are developed in Section 3. In Section 4, we first describe our data set and present some descriptive statistics. We then show our key results and discuss their implications. Section 5 concludes.

## 2 The information content of analyst forecasts

According to the efficient market hypothesis proposed by Fama (1970), stock prices always fully reflect all information available to the capital market. In an informationally efficient market, relevant new information is immediately processed and completely incorporated into stock prices. Price discovery takes place instantaneously, new efficient prices evolve in no time, as the market is able to process any information available correctly, directly and completely. In his seminal article, Fama formulates three forms of market efficiency which

can be distinguished by the information set that is available to investors: In the EMH's weak form, stock prices incorporate only historical information. Therefore, on a weakly efficient market, analyst output, which is fundamentally based on current public or private information, might indeed possess substantial information content. The semi-strong form of the EMH does not only consider historical but also all current information that is publicly available. Besides knowing the past, investors are aware of all relevant public information. Hence, the information is already impounded in stock prices and analyst output can only contain additional content if analysts have access to relevant private information. Finally, on a market that is efficient in terms of the EMH's strong form, stock prices always reflect all information that is publicly or privately available. Therefore, in the case of a strongly efficient market, analyst output has no relevant information content, since literally all past and current information is already reflected in market stock prices.

However, empirical literature has shown that markets are not always fully informationally efficient. Momentum effects, for example earnings momentum or price momentum, provide empirical evidence against both the strong and the medium-strong form of the EMH, showing that new publicly available information is not processed by the market instantaneously (see for example Ball and Brown (1968)'s seminal paper on the post earnings announcement drift and the paper of Givoly and Lakonishok (1979) on forecasts). Indeed, the success of momentum strategies suggests that price discovery on capital markets requires a noticeable amount of time (for example Chan et al. (1996), Givoly and Lakonishok (1980), Stickel (1991), Korajczyk and Sadka (2004) and Czaja et al. (2013)).

The question of whether analysts' output does contain information relevant to the market has been the subject of scientific effort for decades and still remains in academic discussion.

Research in this area is mainly driven by two different methodological approaches: event studies and momentum strategies.

The broad majority of authors confirms the informativeness of various types of analyst forecasts by employing an event study design: Davies and Canes (1978), Elton et al. (1986), Stickel (1995), and Womack (1996) show that stock prices react to financial analysts' recommendation revisions. Their results indicate that positive stock price reactions follow recommendation upgrades while negative reactions follow recommendation downgrades. Chang and Chan (2008) find that market-adjusted returns for stocks that receive downward stock recommendation revisions can be explained by the magnitude of that revisions. In general, analysts' downward stock recommendation revisions provide more influential information to investors than their upward revisions (for example Hirst et al. (1995), Jegadeesh et al. (2004), Mikhail et al. (2004) and Asquith et al. (2005)). As Asquith et al. (2005) show, analysts provide both new information and interpret previously released information. Mikhail et al. (2007) compare the trading behavior of small traders versus large institutional traders and find that both react to analyst reports. But while large traders are net sellers trading on downgrades, small traders are net purchasers following recommendation revisions, regardless of the type of recommendation. These findings show that small investors do not fully account for the effects of analysts' incentives on the credibility of analyst reports and therefore large investors are the more sophisticated processors of information. Besides buy-sell-hold recommendations and their revisions, Givoly and Lakonishok (1979), Abdel-Khalik and Ajinkya (1982), Stickel (1991), and Lys and Sohn (1990) report that analysts' earnings forecasts are informative. As stock prices re-

act to revisions in analysts' earnings per share forecasts, these estimates contain valuable information for investors.

Most closely related to our approach is the study of Brav and Lehavy (2003), who show that stock prices also react significantly to the information in analysts' target prices. The authors accompany their main research design, which again is an event study, with a co-integration approach measuring the long-term relationship between target prices and stock prices. On average, the one-year-ahead target price is 28 percent higher than the current market price and inversely related to firm size.

In the field of trading strategies, Givoly and Lakonishok (1980) present early proof of the existence of earnings forecast momentum and the success of forecast momentum strategies. The authors show that an investor who trades upon publicly available earnings forecast revisions can constantly outperform a buy-and-hold strategy and thereby double his return. In their comprehensive work on momentum strategies, Chan et al. (1996) also report the presence of earnings forecast momentum. Their trading strategy yields return spreads of about 7.7% over the six-month period following the earnings forecast revision. Barber et al. (2001) find that investment strategies based on consensus recommendations yield annual abnormal gross returns greater than four percent. But as these strategies require frequent rebalancing which leads to substantial transaction costs, abnormal net returns are not reliably greater than zero. However, Czaja et al. (2013) show for a highly liquid stock universe that strategies based on earnings forecast momentum are able to generate returns which stay significant not only after common risk adjustments but even after the incorporation of transaction costs. Based on data from the German HDAX, the authors find gross Carhart alphas of up to 22% per year. These results indicate that analysts'



earnings forecasts have a notable information content, which makes momentum strategies on earnings forecasts feasible in portfolio management.

But the relation between analyst forecasts and stock prices is not unidirectional with analyst content exclusively effecting stock market prices: Early findings by Brown et al. (1985) show that sign and magnitude of analysts' forecast revisions are positively associated with sign and magnitude of average cumulative abnormal stock returns for the 12-month period preceding forecast revisions. A lot of survey-based research has been carried out on the question of whether analysts follow stock prices when generating their forecasts. Survey results suggest that analysts do not see stock prices as a source of forecast-relevant information (e.g., Baldwin and Rice (1997) or Brown (1997)). However, as financial analysts regard themselves as important information intermediaries, employing a standard survey design is problematic due to high analyst incentives to avoid revealing their actual use of stock price information. Indeed, Miller and Sedor (2011) provide evidence that analysts do intentionally or unintentionally incorporate stock price information into their earnings forecasts. Their findings show that analyst output does not evolve isolated from the developments on capital markets. While giving relevant information to the market, analysts also incorporate prior stock price movements into their forecasts, thereby reiterating – to an unknown extent – information already known to investors. The authors find that the influence of stock prices on analysts' forecasts is moderated by uncertainty about future earnings with high uncertainty increasing the influence of stock prices on analysts' forecasts. However, although prior stock price movements are reflected to some degree in analyst forecasts, former findings of Abarbanell (1991) show that financial analysts do

not merely re-express information already publicly available but also incorporate private information, which is new to the market.

Nevertheless, although the majority of empirical findings indicate that analysts' forecasts are indeed informative, some voices in the ongoing academic discussion oppose this consensus: Loh and Stulz (2009) show with an event study design that only 12 percent of analysts' recommendation changes significantly impact the stock price of the affected firm. Their findings imply that in turn roughly nine out of ten revisions in analyst recommendations do not noticeably influence the respective company's stock price. Chen et al. (2005) even suggest that analyst recommendations or earnings forecasts are information-free. They report that the price impact of an average analyst recommendation or earnings forecast does not differ from the average stock price movement on non-recommendation days. Also employing an event study design, Altinkilic and Hansen (2009) find that analyst recommendation revisions are associated with economically insignificant mean price reactions and often piggyback on recent news or events, typically downgrading after bad news and upgrading after good news. The authors therefore conclude that revisions in analyst recommendations are usually information-free for investors. Finally, Altinkilic et al. (2009) argue that analyst information processing typically reiterates publicly available information that is already incorporated in stock price. The authors conclude that analysts fail to fulfill their information-intermediary role, since securities markets are informationally too efficient.

In summary, most empirical studies conclude that analyst output does possess relevant information content, although there are also a considerable number of opposite findings. Moreover, academic effort has not provided any conclusive answers to the questions of

whether analyst forecasts incorporate new information faster than the capital markets and to what degree analysts are capable of supporting the process of price discovery. Empirical discourse still lacks a measure to quantify the share analysts have in the process of price discovery.

### 3 Methodology

#### 3.1 Econometric framework

Questions concerning the process of price discovery and informational leadership on capital markets have been discussed in market micro-structure research for decades. If a single security is traded on parallel markets, the corresponding stock prices share a common component, the “fundamental price”. Relevant information can potentially enter stock prices on every single market in the system. The common component evolves due to innovations in any of the involved markets. Market micro-structure research tries to identify where exactly price discovery takes place and which market incorporates relevant information first and in so doing takes informational leadership. Research in this field also tries to clarify the relative share a single market has in the process of price discovery. Two major approaches have evolved to measure informational content on parallel markets:<sup>1</sup> the Information Share (IS) model by Hasbrouck (1995) and the Common Factor Component (CFC) model by Gonzalo and Granger (1995).

In our setting, the first market is the stock exchange, while the second “market” is the analysts’ consensus stock price estimation. Let  $S_t$  denote the stock price at time  $t$  as

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<sup>1</sup>See Peter (2011) and Lien and Shresta (2009) for alternative measures evolved from the IS model.

observed at the stock exchange,  $A_t$  the analyst estimation of the stock price.<sup>2</sup> Since  $S_t$  and  $A_t$  are co-integrated, their monthly changes,  $\Delta S_t = S_t - S_{t-1}$  and  $\Delta A_t = A_t - A_{t-1}$ , can be expressed by a vector error correction model with a co-integrating vector  $\beta = [1; -1]'$ :<sup>3</sup>

$$\begin{bmatrix} \Delta S_t \\ \Delta A_t \end{bmatrix} = \begin{bmatrix} \alpha^S \\ \alpha^A \end{bmatrix} \cdot (S_{t-1} - A_{t-1}) + \sum_{l=1}^L B_l \begin{bmatrix} \Delta S_{t-l} \\ \Delta A_{t-l} \end{bmatrix} + \begin{bmatrix} \epsilon_t^S \\ \epsilon_t^A \end{bmatrix} \quad (1)$$

Here,  $\alpha$  is a (2x1)-vector containing the speed of adjustment coefficients of both markets to the error-correction term  $(S_{t-1} - A_{t-1})$ ,  $B_l$ ,  $l = 1, \dots, L$ , are (2x2)-matrices of autoregressive coefficients up to the maximum lag length  $L$ , and  $\epsilon_t$  denotes a (2x1)-vector of innovations due to new information.

Basically, the right hand side of the VECM consists of two parts: The first one,  $\alpha \cdot (S_{t-1} - A_{t-1})$ , describes the long-term equilibrium dynamics between both time series. Combined with the vector of innovations  $\epsilon_t$ , it serves as the baseline input for the price discovery measures which are presented in the following section. The second part,  $\sum_{l=1}^L B_l [\Delta S_{t-l}; \Delta A_{t-l}]'$ , represents autoregressive terms which describe the transitory short-run deviations of the system, which are caused, for example, by market imperfections.

We perform the standard tests for non-stationarity and co-integration: To ensure that both series are integrated of order 1, we apply the advanced Dickey-Fuller Test for non-stationarity and additionally the Kwiatkowski-Phillips-Schmidt-Shin Test for stationarity.

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<sup>2</sup>We discuss the transformation of earnings per share consensus forecasts into implied stock prices in Section 3.3.

<sup>3</sup>With a general co-integrating vector  $\beta$ , the first term on the right hand side of (1) reads

$$\begin{bmatrix} \alpha^S \\ \alpha^A \end{bmatrix} \cdot \beta' \begin{bmatrix} S_{t-1} \\ A_{t-1} \end{bmatrix}.$$

As the two time series share a common level,  $\beta$  is forced to be  $[1; -1]'$ .

We perform the Johansen Test for co-integration to ensure that  $S_t$  and  $A_t$  are co-integrated. We then choose the lag specification for the vector error correction model as suggested by the Schwarz information criterion (SBIC), before finally estimating the VECM.

## 3.2 Measures of price discovery

### 3.2.1 The common factor component model

The CFC measure is based on the seminal work of Gonzalo and Granger (1995) and focuses on the error correction process as estimated by the VECM; or to be more precise, on the long-term equilibrium dynamics. If the two markets – stock exchange and analysts – process new information at different rates, the long-term equilibrium is disturbed, which means that the error-correction term ( $S_{t-1} - A_{t-1}$ ) moves away from zero. The CFC model measures the contribution of the stock exchange and the analysts to the common factor, that is, the company’s fundamental value, by the speed of adjustment to such a deviation from the long-term equilibrium. The contributions of the two markets to the common factor can be calculated as:<sup>4</sup>

$$CFC^S = \frac{\alpha^A}{\alpha^A - \alpha^S}, \quad CFC^A = \frac{-\alpha^S}{\alpha^A - \alpha^S} = 1 - CFC^S, \quad (2)$$

with  $\alpha$  being the (2x1)-vector of the error correction coefficients derived from the VECM. The bigger  $\alpha^A$  is, the more strongly the analysts correct their estimation towards the stock market price, and vice versa. A market that corrects strongly towards the respective other market merely adopts information already processed by the other side. Or, conversely, a market that does not partake in the error correction process will have an  $\alpha$  of 0 and does

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<sup>4</sup>See for example Peter (2011), Eun and Sabherwal (2003), Harris et al. (2002) or Booth et al. (1999).

not absorb any information already processed by other parties, but only new information. Therefore, that market must be in informational leadership. The market which dominates the process of price discovery will have a small  $\alpha$  and thus a large  $CFC$ , while on the other hand, the market which predominantly follows in the process of price discovery will have a large  $\alpha$  and thus a small  $CFC$ . (Note that due to the asymmetric term  $(S_{t-1} - A_{t-1})$  in (1),  $\alpha^S$  is negative if the stock market corrects towards the analysts.)

### 3.2.2 The permanent-transitory decomposition

The second measure we apply, the information share approach of Hasbrouck (1995), is built upon the idea that a time series can be decomposed into a common permanent component and a transitory component. This idea, which was substantially brought forward by Beveridge and Nelson (1981), is sketched for the univariate case in this subsection.

The permanent component describes the evolution of the fundamental value due to innovations in the information set of the investors engaged in the involved markets, while the transitory component accounts for non-permanent effects which even out in the long-run.

Let

$$\Delta X_t = \mu + \epsilon_t + \psi_1 \epsilon_{t-1} + \psi_2 \epsilon_{t-2} + \dots \quad (3)$$

be the moving-average representation of a covariance-stationary time series  $\Delta X_t$ , describing first-order differences of a series  $X_t$ , which can be thought of as stock prices. For simplicity, we assume  $\mu = 0$ . According to Beveridge and Nelson (1981), the permanent component of a shock  $\epsilon_t$  is defined as the impact of this shock on the long-run conditional

expected value  $E[X_{t+k}|X_0, \dots, X_t]$ , given the information set at time  $t$ , for  $k \rightarrow \infty$ . This expected value can be expressed by the sum of expected first-order differences:

$$E[X_{t+k}|X_0, \dots, X_t] = X_t + E[\Delta X_{t+1} + \dots + \Delta X_{t+k}|X_0, \dots, X_t]. \quad (4)$$

Equation (3) suggests that for each  $j = 1, \dots, k$  the conditional expectation of  $\Delta X_{t+j}$  at time  $t$  is given by

$$E[\Delta X_{t+j}|X_0, \dots, X_t] = \psi_j \epsilon_t + \psi_{j+1} \epsilon_{t-1} + \psi_{j+2} \epsilon_{t-2} + \dots = \sum_{s=j}^{\infty} \psi_s \epsilon_{t+j-s}, \quad (5)$$

as future innovations  $\epsilon_{t+s}$  with  $s > 0$  are unknown with zero expectation. By substituting (5) into (4) and reorganizing the coefficients, we get

$$E[X_{t+k}|X_0, \dots, X_t] = X_t + \left( \sum_{s=1}^k \psi_s \right) \epsilon_t + \left( \sum_{s=2}^{k+1} \psi_s \right) \epsilon_{t-1} + \dots \quad (6)$$

For  $k \rightarrow \infty$ , the long-term impact of a shock  $\epsilon_t$ , that is, its permanent component, is

$$\begin{aligned} & E[X_{t+k}|X_0, \dots, X_t] - E[X_{t+k-1}|X_0, \dots, X_{t-1}] \\ & \xrightarrow{k \rightarrow \infty} X_t - X_{t-1} + \left( \sum_{s=1}^{\infty} \psi_s \right) \epsilon_t - \psi_1 \epsilon_{t-1} - \psi_2 \epsilon_{t-2} - \dots \\ & = \epsilon_t + \left( \sum_{s=1}^{\infty} \psi_s \right) \epsilon_t \\ & = \left( \sum_{s=0}^{\infty} \psi_s \right) \epsilon_t \end{aligned} \quad (7)$$

with  $\psi_0 = 1$ .

In a co-integrated bivariate framework, the same argumentation holds with the scalar moving average coefficients  $\psi_j$  replaced by (2x2) matrices.

### 3.2.3 The information share model

While the CFC model directly measures the contribution of investors and analysts to the common factor, the IS model focuses on the variation in the permanent components of

innovations. The information share measures the contribution of the stock exchange and analysts to the variation of the common factor, accounting for possible correlation between the innovations in the information set at the stock exchange and of analysts.

As the price changes  $\Delta S_t$  and  $\Delta A_t$  are covariance-stationary, the VECM can be expressed in a vector moving average representation according to the Wold theorem (neglecting a constant trend):

$$\begin{bmatrix} \Delta S_t \\ \Delta A_t \end{bmatrix} = \begin{bmatrix} \epsilon_t^S \\ \epsilon_t^A \end{bmatrix} + \sum_{j=1}^{\infty} \Psi_j \begin{bmatrix} \epsilon_{t-j}^S \\ \epsilon_{t-j}^A \end{bmatrix} \quad (8)$$

The (2x2) matrices  $\Psi_j$  are the moving-average coefficients, while  $\epsilon_t$  is a vector of serially uncorrelated innovations in the information set of both markets with zero mean and covariance matrix  $\Omega$ . We apply the Beveridge-Nelson decomposition and express equation (8) in terms of the series' permanent and transitory components:

$$\begin{bmatrix} \Delta S_t \\ \Delta A_t \end{bmatrix} = \left( \sum_{j=0}^{\infty} \Psi_j \right) \begin{bmatrix} \epsilon_t^S \\ \epsilon_t^A \end{bmatrix} + \sum_{j=1}^{\infty} \Psi_j^* \begin{bmatrix} \epsilon_{t-j}^S \\ \epsilon_{t-j}^A \end{bmatrix} \quad (9)$$

with  $\Psi_0 = I$  and some coefficient matrices  $\Psi_j^*$ . As seen in Section 3.2.2,  $\bar{\Psi} := \sum_{j=0}^{\infty} \Psi_j$  measures the long-run impact of an innovation  $\epsilon_t$  to the level of the price series. As Baillie et al. (2002) show,  $\bar{\Psi}$  can be directly derived from the VECM coefficients  $\alpha = [\alpha^S; \alpha^A]'$  and  $\beta = [1; -1]'$ :

$$\bar{\Psi} = \Pi \beta_{\perp} \alpha'_{\perp} \quad (10)$$



with a constant  $\Pi$ , where  $\alpha_\perp$  and  $\beta_\perp$  are orthogonal vectors to  $\alpha$  and  $\beta$ , respectively.<sup>5</sup>

Since  $\beta = [1, -1]'$ ,  $\beta_\perp = [1, 1]'$ . We can therefore rewrite equation (10) as:

$$\bar{\Psi} = \Pi \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} \gamma_S \\ \gamma_A \end{bmatrix}' = \Pi \begin{bmatrix} \gamma_S & \gamma_A \\ \gamma_S & \gamma_A \end{bmatrix} \quad (11)$$

with  $\gamma_S$  and  $\gamma_A$  being the components of  $\alpha'_\perp$ .<sup>6</sup>

Essentially,  $\bar{\Psi}\epsilon_t$  describes the long-run impact of an innovation on any of the two price series. As Equation (11) shows, the rows of  $\bar{\Psi}$  are identical, which implies that the long run impact of an innovation  $\epsilon_t$  in any of the two price series is identical also.

Letting  $\psi := [\psi_S; \psi_A] := \Pi[\gamma_S; \gamma_A]$  denote the common row vector in  $\bar{\Psi}$ , the scalar  $\psi\epsilon_t$  is the permanent component of an innovation caused by new information. Its variance is  $\psi\Omega\psi'$ . If  $\Omega$  is diagonal, which means that innovations in the information set of investors and analysts are uncorrelated, it is the sum of two terms:

$$\psi\Omega\psi' = \psi_S^2\sigma_S^2 + \psi_A^2\sigma_A^2. \quad (12)$$

Following Hasbrouck (1995), a market's contribution relative to the total variance is defined as its information share:

$$IS^S = \frac{\psi_S^2\sigma_S^2}{\psi_S^2\sigma_S^2 + \psi_A^2\sigma_A^2}, \quad IS^A = \frac{\psi_A^2\sigma_A^2}{\psi_S^2\sigma_S^2 + \psi_A^2\sigma_A^2} = 1 - IS^S. \quad (13)$$

If innovations in the information set of investors and analysts are not uncorrelated,  $\Omega$  is not diagonal. In this case, Hasbrouck suggests calculating lower bounds  $[IS]$  for the

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<sup>5</sup>These vectors are only unique up to a multiplicative constant. For the definition of the information share, this constant is however arbitrary, as it cancels out in the defining equation.

<sup>6</sup>Note that these components are identical to the common factor components  $CFC^S$  and  $CFC^A$  up to a multiplicative factor.

information shares by considering only the “pure” variance of a market that is not affected by the correlation  $\rho$  to the other market. In the bivariate case, the upper bounds  $[IS]$  are simply defined as the complements to the lower bounds of the respective other market:<sup>7</sup>

$$[IS^S] = \frac{\psi_S^2 \sigma_S^2 (1 - \rho^2)}{\psi \Omega \psi'}, \quad [IS^A] = 1 - [IS^S], \quad (14)$$

and

$$[IS^A] = \frac{\psi_A^2 \sigma_A^2 (1 - \rho^2)}{\psi \Omega \psi'}, \quad [IS^S] = 1 - [IS^A]. \quad (15)$$

Hasbrouck then approximates the actual information share as the average of the upper and lower bound.

It is obvious that the upper and lower bounds can substantially differ if the correlation is large. In these cases, information shares defined as the average of upper and lower bounds should only be interpreted with care.

### 3.2.4 Comparison

Both the IS model and the CFC model provide relative measures and are fundamentally based upon the concept of co-integration and a vector error correction model. Incorporating the error correction behavior of both price series and their co-integrating long-term relation provided by the VECM, both models focus on the question of informational leadership in terms of “Who moves first?”; or to be more precise, of informational content.

The IS model proposed by Hasbrouck (1995) is based on an implicit and unobservable efficient price (the above-described common permanent component), which is common to

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<sup>7</sup>Note that in the case of correlated innovations, the variance of the permanent component is calculated as  $\psi \Omega \psi' = \psi_S^2 \sigma_S^2 + \psi_A^2 \sigma_A^2 + 2\rho \psi_S \sigma_S \psi_A \sigma_A$

all markets. The information share of a particular market is defined as the proportional contribution of that market's innovations to the innovation in the common efficient price. In the CFC model, Gonzalo and Granger (1995) define the common factor (again the common permanent component) as being a linear combination of the two market prices. As Baillie et al. (2002) state, the common factor might be envisioned as the price of a portfolio of all involved stocks, weighted by a common factor coefficient vector.

The two approaches mainly differ in the way they treat the variance of the innovations. The CFC model only incorporates the weight that an innovation on a certain market has in the increment of the efficient price. The variance of that innovation is ignored. In contrast, the IS model measures the share that a certain market has in the total variance of innovations in the efficient price. According to de Jong (2002), both price discovery models have their advantages: Gonzalo and Granger aim at constructing a common permanent component that is a simple linear combination of the involved price series. Their model indicates, how much weight to place on the innovations of a certain market in the construction of the efficient price. Hasbrouck's definition focuses on the amount of variation in the efficient price, and how much of this variation is explained by the price changes on a certain market. By this means, only the IS model accounts for correlation in the innovations. Baillie et al. (2002) show that the IS model and the CFC model are directly related and provide complementary insights into the process of price discovery on parallel markets. Both models yield similar results if the innovations are uncorrelated between the parallel markets and if the variance of the innovations is equal in level in all markets. However, their results might diverge due to substantial differences

in the level of variance in the innovations or due to the presence of substantial correlation between the involved markets.

Parallel markets may not only include different stock markets, but also markets for derivatives such as forwards, futures or options. Successive literature has adapted this idea (for example Booth et al. (1999), Chakravarty et al. (2004) or Figuerola-Ferretti and Gonzalo (2010)). But the concept of parallel markets does not only apply for a single security or its derivatives: Its key prerequisite is that the fundamentals driving the evolution of all variables in the system must be the same. Therefore, the informational linkage between all involved variables is essential. As both stock prices and analyst consensus earnings forecasts are basically driven by the same underlying fundamentals, they indeed are informationally linked. We can therefore apply the concept of parallel markets in our setting to identify the share that analysts and investors on capital markets have in the process of price discovery.

### 3.3 Scaling analyst consensus forecasts to stock price level

As discussed, we expect the price of a stock and the respective analyst consensus forecast to share a common component, since both depend on the same underlying. Therefore, we transform the earnings per share estimates provided by the analysts into implied stock prices which represent the expectations of the analysts about what the actual stock price should be. The same requirement of a (non-linear) transformation of a time series occurs in price discovery studies involving derivative markets. We follow the idea of Chakravarty et al. (2004), who use an option model to convert option prices into implied stock prices.

Since our input data are stock prices and EPS consensus forecasts, we apply an enterprise valuation model to transform the latter ones into implied stock prices.

Let  $E\hat{P}S_t$  be the earnings per share consensus forecast provided by the analysts at time  $t$ . To relate the EPS forecast to the stock price, we assume a simple growth model in the spirit of Gordon (1959): EPS increase with a growth rate  $g_t$ , and the free cash flow is a constant share  $\lambda_t$  of the EPS. With the cost of capital,  $c_t$ , the EPS estimate translates into a stock price estimate via

$$A_t = \hat{S}_t = \frac{\lambda_t E\hat{P}S_t}{c_t - g_t} = M_t \cdot E\hat{P}S_t \quad (16)$$

with a multiplier  $M_t = \lambda_t (c_t - g_t)^{-1}$ .

The problem is that we do not know the growth rate  $g_t$ , nor the share  $\lambda_t$ , nor the cost of capital  $c_t$ . However, we do not need to estimate these parameters exogenously, but invert (16) with a lagged time parameter  $t - s$ , using the observed exchange stock price  $S_{t-s}$ :

$$M_t = \frac{S_{t-s}}{E\hat{P}S_{t-s}}. \quad (17)$$

This idea of using lagged implied parameter estimates in a simple model relationship between the two observable time series (here, stock prices and EPS forecasts) is borrowed from Chakravarty et al. (2004) (among others). The same problem of related time series that differ in level and possibly in their long-term relationship occurs in the analysis of stock prices and derivative prices. In such a setting, it is common practice to use a simple model that relates the two time series (for example, the Black-Scholes model) and to estimate the implied model parameter (the implied volatility) by lagged values of the time series.

Transferred to our setting, the simple model is the Gordon growth model (16), and the implied parameter is the multiplier  $M_t$ . As with the Black-Scholes model in the case of derivative prices, we do not claim that the Gordon growth model accurately holds. It is merely a vehicle to relate the two time series to each other. Therefore, the implied parameter may vary over time. The crucial point is that the VECM adequately covers the co-integrated relationship between the two price series.

However, if the lag parameter  $s$  is too small, exchange stock price changes are wrongly reflected in implied analyst stock price changes. Formally expressed,  $s$  must be long enough to guarantee uncorrelated error terms  $\epsilon_t$  and  $\epsilon_{t-s}$ . On the other hand,  $s$  must not be too large to ensure that the applied multiplier  $M_t$  is not outdated. We calculate rolling average implied multipliers  $M_t$  with lags of 12 to 24 months, that is,

$$A_t = M_t \cdot \hat{EPS}_t \quad (18)$$

with

$$M_t = \frac{1}{13} \sum_{s=12}^{24} \frac{S_{t-s}}{\hat{EPS}_{t-s}}. \quad (19)$$

Within our robustness analysis, we also test multipliers calculated with lags of 6 to 12 months.

Thus,  $A_t$  denotes the series of analyst consensus EPS estimates, scaled to stock price level. To measure the share that analysts' EPS forecasts have in the process of price discovery, we now use  $S_t$  and  $A_t$  as input data for our price discovery models and compute Hasbrouck (1995) Information Shares and the Gonzalo and Granger (1995) Common Factor Components (CFC).

## 4 Empirical study

### 4.1 Data

We focus on the US market and collect data for all 100 companies that were listed in Standard & Poor's S&P 100 Index in 2012. Our dataset is based on monthly data and spans 36 years, including monthly analyst consensus EPS forecasts and stock prices from January 1976 through March 2012. The analyst consensus forecasts are rolling 12-month-ahead estimates. They are extracted from the original estimates for the current and forthcoming fiscal year as a weighted average.<sup>8</sup>

We reduced our sample by those companies that did not fulfill the baseline requirements of our analysis: Six companies were dropped because of too short time series. Moreover, as the presence of statistically significant co-integration between  $S_t$  and  $A_t$  is vital for our model framework, we eliminated those firms for which the Johansen co-integration test did not clearly identify a co-integrating relation. Our final sample therefore consists of 75 companies. All time series are logarithmized to meet the requirements of the linear econometric model.

[Insert Table 1 about here.]

Table 1 presents some descriptive statistics. The consensus EPS estimate is based on up to 50 individual analyst forecasts. Averaged over time, the firm with the minimum coverage is followed by 12 individual analysts, while the firm with the maximum coverage

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<sup>8</sup>For example, three months before fiscal year-end, the rolling 12-month estimate is 3/12 of the EPS estimate for the current year plus 9/12 of the estimate for the forthcoming year.

is followed by 30 individual analysts. The average standard deviation of the consensus EPS estimate by firm serves as a proxy for the level of disagreement among analysts about the fundamental value of a firm. We scale this measure by the respective company's stock price to make it comparable in the cross-section.

## 4.2 Informational leadership

To measure the information content of analyst consensus forecasts and answer the question of informational leadership, we compute common factor components and information shares for all firms in our sample. The raw results exhibit *positive* values of  $\alpha^S$  for a number of firms, yielding *negative* common factor components of the analysts. In these cases we set  $CFC^A$  to zero, as these values should be in the interval between 0 and 1.

Table 2 shows the firm-level results and some overall statistics of our analysis. Also reported are upper and lower bounds for the analysts' information share,  $[IS^A]$  and  $\lfloor IS^A \rfloor$  respectively. Common factor components and information shares being significantly larger than zero are indicated.

[Insert Table 2 about here.]

We first note that upper and lower bounds of the analysts information share  $IS^A$  are close together for most companies with a mean deviation of 1.22%. As discussed in Section 3.2.3, upper and lower IS bounds deviate in the presence of cross-correlated residuals  $\epsilon_t$ . Our results therefore indicate that the level of cross-correlation is low, underlying the validity of the information share concept.



On average, price discovery takes place largely on the stock market itself. The common factor components model allocates 82% of price discovery to investors on stock markets, the information share measures even more than 95%. Thus on average, stock markets take informational leadership relative to the analysts. Nevertheless, both price discovery measures indicate that analysts do take part in the process of price discovery. The information share of analysts is significant at the 10% level for 16 out of the 75 firms, at the 5% level for 12 firms, and at the 1% level for 3 firms. It should be noted that even if there was no participation of analysts in the process of price discovery at all, randomly 7.5 out of 75 firms would be expected to exhibit significance at the 10% level (3.75 at the 5% level and 0.75 at the 1% level, respectively). The actual figures are larger, showing that the measured significance is not artificial at least for a small number of companies. Thus, with an average CFC of 18% and an average IS of nearly 5%, analyst consensus EPS forecasts are informative for some firms, and analysts are able to input a noticeable amount of information into a market's stock prices.

Our firm-level results show that the analysts' weight in the process of price discovery varies significantly in the cross-section: On firm-level,  $CFC^A$  ranges between 0 and 59.3% (Norfolk Southern Railway) ( $IS^A$  between 0 and 33.3%, respectively). Obviously, for some firms, analysts are not able to provide any new information relevant to investors, while for others they speed up price discovery considerably. For companies like Norfolk Southern Railway, Citigroup, Raytheon and the United Technologies Corporation analysts potentially even take informational leadership with  $CFC^A$  exceeding 50%.

Summing up, both the information share and the common factor component indicate on average that analyst consensus EPS forecasts do have a measurable information content

for investors on capital markets. Thus, in a number of cases, capital markets incorporate certain information more slowly than the analysts. This can be for two possible reasons: First, investors might not have access to all relevant information available and therefore need to react to the relevant information in analyst consensus forecasts that is missing in their own information set. This would imply the presence of private information and thus challenge the concept of strong informational efficiency. Second, compared to analysts, investors might possess minor skills in processing relevant information, thereby incorporating parts of publicly available information slower than analysts. In this setting, investors might even have access to all relevant information, but due to their minor information processing skills, they react to new information slower than the analysts. This implies that stock prices do not incorporate new information instantaneously. This second interpretation would oppose even the concept of medium strong informational efficiency.

In any case, information shares considerably greater than zero (for some firms) imply that the US stock market either does not have all relevant information available or does not process all information available instantly. Thus our results oppose the EMH – at least in its strong form – and indicate that on average analysts are important information intermediaries, and that investors on the US stock market process information in analyst consensus EPS forecasts.

However, as the average share of analysts is substantially lower than 50% for both of our information measures, analysts are not generally able to lead investors on capital markets.

Summing up, two major conclusions can be drawn from our analysis:

- For the majority of firms, analysts do not provide a significant share of information in the price discovery process.

- For more than one fifth of all S&P 100 firms however, analysts consensus EPS forecasts do possess a measurable information content and reflect parts of relevant information faster than stock prices. The presence of analysts helps speed up the process of price discovery, as parts of the US stock market are not efficient in terms of the strong-form EMH and might not be efficient in terms of the semi-strong form.

### 4.3 Impact factors on analysts' information share

As shown in the previous section, for the majority of companies, analyst consensus forecasts hardly provide any additional information content at all, while for others, they might even take informational leadership relative to stock prices. In this section, we focus on the question of what firm-specific characteristics impact the amount of information that the analysts are able to bring into the capital market. In particular, we analyze the impact of company size, company age, analyst coverage and mean consensus forecast variation on our price discovery measures.

We measure the size of a company by its logarithmized mean market capitalization throughout the sample period and its age in logarithmized years between firm foundation and the end of our sample period (2012). The analyst coverage of a company is measured by the mean number of estimates constituting the consensus forecast. Finally, variation in the consensus forecast of a company is quantified by the mean standard deviation of its consensus EPS forecast, scaled by its stock price. We regress the information measures IS and CFC on these potentially influencing factors within a tobit regression framework, which is left-censored at zero. Table 3 shows the results.

[Insert Table 3 about here.]

Both regressions indicate that analyst coverage has a significant negative impact on the share of the analysts in the process of price discovery. That is, companies with high analyst coverage tend to have a low  $CFC^A$  and  $IS^A$ . The more forecasts by individual analysts constitute the consensus estimate, the less information does it contain for investors on capital markets. Here, our results might provide surprising evidence on first sight: Intuitively, the larger the number of following analysts, the more expertise gets involved in the valuation process of the company's future prospects and the more informative should be the resulting consensus EPS forecast.

But our finding appears to be puzzling only at first glance: An extensive strand of literature is concerned with analyst incentives and behavioral biases (see for example Van Campenhout and Verhestraeten (2010), who provide a recent literature review on herding among financial analysts). High analyst coverage results in a strong consensus forecast formed by a large number of analysts. For individual analysts, incentives are high to stick to a strong consensus constituted by a large number of individual analysts – even if the individual analyst's estimate significantly differs from the consensus estimate. In this case, psychological constraints such as fears of dismissal or career concerns might lead analysts to show herding behavior and revise their forecasts towards the consensus (see for example Hong et al. (2000) or Trueman (1994)). As a result, the consensus forecast becomes biased, since new but contradictory information relevant to the market is excluded. In contrast, if the number of analysts covering a company is low, the consensus forecast is weak as every single forecast notably affects the consensus estimate. This makes individual analysts more visible and could potentially increase their perception of responsibility towards the public. Moreover, low analyst coverage makes it easier for individual analysts

to oppose the consensus and stick to their own forecasts: It might be less problematic to contradict two colleagues than twenty. Hence low analyst coverage would lead to less biased consensus forecasts.

The results are robust with respect to the choice of the implied multipliers  $M_t$ . We repeated the analysis based on a shorter lag-length of only six months with  $M_t$  incorporating lags of 6 to 12 months. The results of the cross-sectional regression are shown in the last two columns of Table 3. Our findings stay statistically significant.

## 5 Conclusion

In this paper, we analyzed the information content of monthly analyst consensus forecasts for one-year-forward earnings per share (EPS). Based on the Gonzalo-Granger CFC model and the Hasbrouck IS model we measured the relative share the analysts and the stock market have in the process of price discovery. We focused on large US companies listed in the S&P 100 Index and conducted a long-term analysis spanning a 36-year period.

We find that analyst consensus EPS forecasts only contain a small amount of information that is new to the market on average: Following the approach of Gonzalo and Granger, 82% of price discovery takes place on the stock market, while the analysts provide 18%. The degree to which analysts are capable of supporting the process of price discovery and even taking informational leadership varies significantly in the cross-section: For the major part of our sample, stock markets show common factor components larger than 50%. For only 16 out of 75 firms, analysts provide a significant share of information in the price discovery process.

We find evidence that analyst coverage significantly impacts the relative amount of information contained in analyst output: The lower the mean analyst coverage is for a company, the more information enters its stock price via analyst consensus EPS forecasts and the larger is the analysts' share in price discovery. This might be due to individual analysts fearing to swim against a strong consensus estimate that is based on a large number of individual forecasts. In the case of high analyst coverage, a higher level of analyst herding would therefore cause the consensus EPS forecast to be more biased than in the case of low analyst coverage. As a result, the stronger bias incorporated in a high-coverage forecast reduces its informativeness for investors on capital markets.

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$n = 75$	Market Cap	Age	Coverage	Forecast Std.
Mean	36.5	87	19.7	0.00567
Std.	102.0	49	4.4	0.00481
Min.	3.5	10	12.5	0.00089
max.	885.0	228	30.6	0.02276

**Table 1.** *Descriptive statistics. Market Cap is the average market capitalization in Billion USD, Age is the company's age at the the end of our sample period in 2012, measured in years, Coverage is the average number of estimates constituting the analyst consensus forecast, Forecast Std. is the average standard deviation in the estimates constituting the consensus forecast, scaled by the stock price.*

	$CFC^A$	$IS^A$	$[IS^A]$	$[IS^A]$
3M	24.7	1.08	1.14	1.02
Alcoa	11.2	0.74	0.86	0.62
Altria Group	46.8*	33.31*	34.01	32.61
American Electric Power	14.3	0.18	0.28	0.08
American Express	0.0	0.00	0.00	0.00
Apache	0.0	0.00	0.00	0.00
AT&T	8.6	0.16	0.16	0.15
Avon Products	23.1	0.67	0.86	0.48
Baker Hughes	22.8	2.37	2.41	2.32
Bank of America	0.0	0.00	0.0	0.00
Bank of New York Mellon	1.7	0.04	0.08	0.00
Baxter International	0.0	0.00	0.00	0.00
Boeing	8.6	0.42	0.65	0.19
Bristol-Myers Squibb	0.0	0.00	0.00	0.00
Caterpillar	10.3	1.50	1.80	1.21
Chevron Corporation	21.1	2.31	2.66	1.96
Citigroup	52.2*	23.59*	27.29	19.88
Coca-Cola Company	0.0	0.00	0.00	0.00
Colgate-Palmolive	4.6	0.03	0.03	0.02
ConocoPhillips	16.8	2.10	2.96	1.23
CVS Caremark	34.6	2.59	2.94	2.24
Dell	0.0	0.00	0.00	0.00
Devon Energy	0.0	0.00	0.00	0.00
Dow Chemicals	0.0	0.00	0.00	0.00
Emerson	37.8	5.01	6.08	3.94
Entergy	45.9	5.42	6.22	4.62
Exelon	44.9	7.35	9.33	5.37
Exxon Mobil	0.0	0.00	0.00	0.00
FedEx	46.4*	12.90*	13.21	12.59
Freeport-McMoRan	0.0	0.00	0.00	0.00
General Dynamics	46.2**	13.45**	15.59	11.31
General Electric	0.0	0.00	0.0	0.00
Gilead Sciences	33.5	8.81	10.95	6.67
Halliburton	0.0	0.00	0.00	0.00
Heinz Company	0.0	0.00	0.0	0.00
Hewlett-Packard	13.2	3.43	4.91	1.95
Home Depot	0.0	0.00	0.00	0.00
Honeywell International	46.4 <sup>o</sup>	6.94 <sup>o</sup>	7.86	6.03
IBM	20.2	3.30	4.02	2.59
Intel	0.6	0.34	0.66	0.01
Johnson & Johnson	6.1	0.09	0.13	0.05
JP Morgan Chase & Co.	34.6 <sup>o</sup>	10.10 <sup>o</sup>	11.68	8.52
Kraft Foods	39.7	6.53	8.29	4.77
Lockheed Martin	0.0	0.00	0.00	0.00

– Table 2 continued –

	$CFC^A$	$IS^A$	$[IS^A]$	$[IS^A]$
Lowe's	19.1	2.50	3.08	1.93
McDonald's	28.5	1.58	1.80	1.36
Medtronic	0.0	0.00	0.00	0.00
Merck & Co.	0.0	0.00	0.00	0.00
Monsanto	16.4	1.17	1.54	0.79
Morgan Stanley	20.5	4.29	7.47	1.10
National Oilwell Varco	13.1	1.28	2.03	0.52
Nike	35.2	5.08	5.64	4.52
Norfolk Southern Railway	59.3**	27.48**	31.85	23.11
Occidental Petroleum	0.0	0.00	0.00	0.00
Oracle	0.0	0.00	0.00	0.00
PepsiCo	42.3 <sup>o</sup>	6.16 <sup>o</sup>	6.50	5.81
Pfizer	0.0	0.00	0.00	0.00
Procter & Gamble	0.0	0.00	0.00	0.00
Qualcomm	0.0	0.00	0.00	0.00
Raytheon	55.4*	21.76*	24.83	18.69
Schlumberger	11.5	0.78	1.23	0.33
Southern Company	0.4	0.44	0.88	0.00
Sprint Nextel	34.4*	22.33*	25.09	19.57
Target Corporation	48.0*	7.52*	8.15	6.89
Texas Instruments	0.0	0.00	0.00	0.00
Union Pacific	47.1*	15.18*	16.58	13.79
United Technologies Corporation	58.5*	15.73*	17.91	13.55
UnitedHealth	5.5	0.12	0.23	0.01
US Bancorp	0.0	0.00	0.00	0.00
Verizon Communications	19.9	0.21	0.42	0.01
Walt Disney	43.2 <sup>o</sup>	9.52 <sup>o</sup>	9.53	9.52
Wells Fargo	34.8*	15.73*	17.35	14.12
Weyerhaeuser	42.6**	29.12**	29.22	29.02
Williams Companies	0.0	0.00	0.00	0.00
Xerox	0.0	0.00	0.00	0.00
Mean	18.0	4.57	5.18	3.96
Standard deviation	19.3	7.73	8.43	7.09
Min	0.0	0.00	0.00	0.00
1Q	0.0	0.00	0.00	0.00
Median	11.5	0.67	0.86	0.33
3Q	34.8	6.16	6.50	5.81
Max	59.3	33.31	34.01	32.61

**Table 2.** Common factor components ( $CFC$ ) and information shares for the analysts by company. For the information shares, upper and lower bounds are reported. All values in percent.  $CFC^A$  and  $IS^A$  significantly different from zero are indicated by <sup>o</sup> at the 10% level, \* at the 5% level and \*\* at the 1% level.

	Main Set		Robustness	
	$CFC^A$	$IS^A$	$CFC^A$	$IS^A$
<i>meanCompanySize</i>	-0.0237 (0.0459)	-0.0015 (0.0187)	+0.0118 (0.0438)	+0.0412 (0.0314)
<i>meanAnalystCoverage</i>	-0.0187* (0.0078)	-0.0058 <sup>°</sup> (0.0029)	-0.0209** (0.0067)	-0.0115** (0.0042)
<i>meanForecastStd</i>	-1.87 (7.48)	+4.29 (3.56)	+2.33 (1.69)	+2.60 <sup>°</sup> (1.43)
<i>companyAge</i>	-0.067 <sup>°</sup> (0.039)	-0.011 (0.017)	-0.079* (0.039)	-0.047* (0.023)
<i>constant</i>	+0.849*** (0.253)	+0.160 (0.109)	+0.732** (0.225)	+0.267* (0.113)

Standard errors in parentheses

<sup>°</sup>  $p < 0.1$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

**Table 3.** Results of the impact regressions, based on both a rolling 12-month multiplier  $M_t$  lagged by 12 to 24 months (Main Set) and a rolling 6-month multiplier  $M_t$  lagged by 6 to 12 months (Robustness). *meanCompanySize* is the average log market capitalization, *meanAnalystCoverage* the average number of estimates constituting the consensus forecast, *meanForecastStd* is the average standard deviation of the consensus forecast, scaled by the stock price, *companyAge* is the logarithmized number of years since foundation at the end of the sample period in 2012. Robust standard errors are computed adjusting for heteroscedasticity according to White (1980).