Does Management Forecast Guidance Impair the Usefulness of Analyst Forecasts in Firm Valuation?

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Analyst earnings forecasts are an important input to the Residual Income Valuation model; however, these forecasts are increasingly subject to management guidance. This study examines the impact of management forecast guidance on the usefulness of analyst earnings forecasts in firm valuation. It finds that valuation models estimated using guided forecasts have less ability to explain stock price and predict future returns through value-to-price ratios than valuation models estimated using non-guided forecasts. These results provide evidence that management forecast guidance reduces the usefulness of analyst forecasts in firm valuation and impairs the performance of forecast-based valuation models to predict firm value.

Keywords: firm valuation; analyst forecast; expectations management

Introduction

Ohlson (1995) provides a conceptual framework for relating accounting earnings to firm value. Analyst earnings forecasts are important inputs to the empirical implementation of Ohlson's (1995) residual income valuation model (RIM). In particular, Dechow et al. (1999) and Frankel and Lee (1998) show that intrinsic value metrics (V) estimated using analyst forecasts are better than other value metrics at explaining contemporaneous stock price (P) and predicting future returns through intrinsic value-to-price (V/P) ratios. This establishes the *usefulness* of analyst forecasts in firm valuation.

While analyst earnings forecasts have gained popularity among researchers and investors, analyst forecasts are increasingly subject to management guidance. According to the surveys by NIRI, around 79% of firms provide some form of earnings guidance. The ability of valuation models to estimate firm value is affected by the quality of model inputs. Gaio and Raposo (2014) report that earnings quality affects firm valuation. However, existing valuation studies have not considered the impact of forecast quality on the performance of forecast-based valuation models. Kasznik and McNichols (2002) call for future studies to investigate the consequences of management manipulation on firm valuation. In response, this paper examines the impact of management forecast guidance on the usefulness of analyst forecasts in firm valuation.

Whether management forecast guidance improves or impairs the usefulness of analyst forecasts in firm valuation depends on the purpose of management forecast guidance. Most studies in the expectations management literature, notably Bartov et al. (2002) and Richardson et al. (2004), take the view that management issues earnings guidance for the purpose of dampening analyst earnings expectations to produce beatable forecasts upon earnings release. This view is supported by subsequent studies. For instance, Graham et al. (2005) document in a survey study that CFOs admit that they would guide analyst forecasts down to artificially low levels in order to meet or beat analyst earnings expectations (hereafter, *MBE*); Burgstahler and Eames (2006) and Koh et al. (2008) document that firms manage analyst forecasts downward to just meet analyst expectations; and Kross et al. (2011) find that firms that consistently MBE are more likely to issue bad-news management forecasts to guide down analysts' expectations and produce beatable forecasts. Similar findings are reported in the UK context (e.g., Brown and Higgins, 2005; Athanasakou et al., 2009).

However, not all forecast guidance is issued for the purpose of manipulating analysts' earnings expectations. Several studies in the voluntary disclosure literature document that sometimes firms issue earnings guidance to truthfully communicate inside information and abate analyst over-optimism. In particular, Kasznik and Lev (1995), Coller and Yohn (1997), and Hutton, Miller, and Skinner (2003) document that firms issue earnings guidance to reduce information asymmetry between the firm and the market. Lansford, Lev and Tucker (2013) document that firms' voluntary earnings guidance assists analysts and investors in predicting future operating performance. Such earnings guidance reduces information asymmetry and improves forecast accuracy (Lang and Lundholm 1996).

Whether management forecast guidance improves or impairs the usefulness of analyst forecasts in firm valuation depends on the relative mix of these two types of guidance. That is, if firms issue earnings guidance mainly for the purpose of walking down analyst expectations to produce beatable forecasts at earnings release, then forecast guidance will reduce the ability of analyst forecasts to convey information about firms' future performance and therefore impair the usefulness of analyst forecasts in firm valuation. This hypothesis is formally stated as follows:

***H**: Management forecast guidance impairs the usefulness of analyst earnings forecasts in forecast-based valuation models.*

However, if firms issue earnings guidance mainly for the purpose of communicating inside information and correcting analyst optimism, then such guidance will improve the usefulness of analyst forecasts in firm valuation. The alternative hypothesis is stated as follows:

***H(a)**: Management forecast guidance improves the usefulness of analyst earnings forecasts in forecast-based valuation models.*

Research Design

This section describes the research design including estimating value metrics, the forecast guidance measure, the intrinsic value measure, and the empirical analyses.

Estimating intrinsic value metrics (V)

Following Dechow et al. (1999), this study uses Ohlson's (1995) RIM as the valuation framework to estimate V. Specifically, at the end of each forecast year *t*, V is constructed for each firm using earnings in year *t-1*, book value at the beginning of year *t*, and the consensus forecast for year *t*'s earnings measured at the end of year *t* (prior to the earnings announcement). Better V metrics have greater ability to explain contemporary stock price and predict future returns through V/P ratios (Frankel and Lee, 1998; Lee et al., 1999; Dechow et al., 1999; Sohn, 2012). In particular, Lee et al. (1999) argue that although accounting regulators are more concerned with the value relevance of accounting-based measures and portfolio managers are more interested in V's predictive power, both stock tracking ability and return prediction power are desirable properties of the V metrics; they find that better V performs better in both dimensions. Therefore, this study employs both analyses—it investigates the impact of forecast guidance on the usefulness of analyst forecasts by comparing the performance of V estimated using guided versus non-guided forecasts to explain stock price and predict future returns through V/P ratios.

Forecast guidance measure

Firms can use different channels to guide analyst expectations. In particular, they can issue management forecasts or host conference calls, or guide analyst expectations via private conversations with analysts in informal settings. This study constructs a measure of management forecast guidance that captures management guidance through different channels. Prior research has developed two main approaches to capture both the explicit and implicit forecast guidance. In the first approach, developed by Bartov et al. (2002) and later adopted by Brown and Pinello (2007), Bartov and Cohen (2009), etc., forecast guidance is suspected when analyst forecasts are optimistic at the beginning of a period and pessimistic at the end of the period. This approach identifies both management's motive to guide (in the form of initial optimism) and the result of management forecast guidance (in the form of a downward forecast revision). However, analysts may voluntarily revise down their forecasts to incorporate firm-level, industry-level or even market-level bad news occurring during the year - such downward revision is not driven by management forecast guidance. This approach does not distinguish news-driven revision from guidance-driven revisions.

In the second approach, developed by Matsumoto (2002) and subsequently adopted by Brown and Higgins (2005), Koh et al. (2008), etc., forecast manipulators are defined to be the firms whose last consensus forecasts are lower than the expected forecasts. Matsumoto (2002) constructs the expected forecast by modeling the seasonal changes in earnings as a function of prior seasonal changes in earnings and the cumulative returns during the year. The strength of this approach is that it takes into account the effect of economy-wide and/or firm-specific bad news on analyst forecasts. However, this approach does not consider whether there are guidance-driven downward revisions in analyst forecasts throughout the year.

The above discussion suggests that while each approach has its strengths, neither provides a desirable measure of forecast guidance in the context of this study. Therefore, this study builds on these two approaches to develop a measure that attempts to capture the notion of management forecast guidance as defined in this study. Figure 1 illustrates the timeline for the forecast-related measures. Forecast year *t* starts 360 days prior to the announcement of year *t*'s earnings and ends one day prior to the earnings announcement. A forecast year consists of 12 forecast months, each month represents a 30-day period. To avoid the staleness problem[1] often associated with the consensus forecasts published by the Institutional Brokers' Estimate System (IBES), the last forecast issued by each analyst within each time interval is used to compute the consensus forecast for that time interval. In particular, this study defines the consensus forecast at the beginning of the year for firm *i* in year *t* (AF_{it}^{early}) as the median of the latest forecast issued by each analyst in the first three months of year *t*, and the "late consensus forecast" for firm *i* in year *t* (AF_{it}^{late}) as the median of the latest forecast issued by each analyst in the last three months of year *t*. This study then uses the early and late consensus forecasts to identify expectations manipulators in the following two steps.

Step 1: Establish the motive to guide

Following Bartov et al. (2002), this study identifies a firm's motive to guide analyst expectations by the initial optimism in analyst forecasts at the beginning of the year. Specifically, previous year's reported earnings (x_{it-1}) is used as a proxy for the manager's earnings expectation at the beginning of the year; this study then compares the consensus forecast at the beginning of the year (AF_{it}^{early}) with the previous year's earnings and classify firm-years with $AF_{it}^{early} > x_{it-1}$ as possible forecast guiders.

[1] Abarbanell and Bernard (1991) note that the staleness problem arises because the IBES consensus forecast includes forecasts that are made in prior months and are not yet updated.

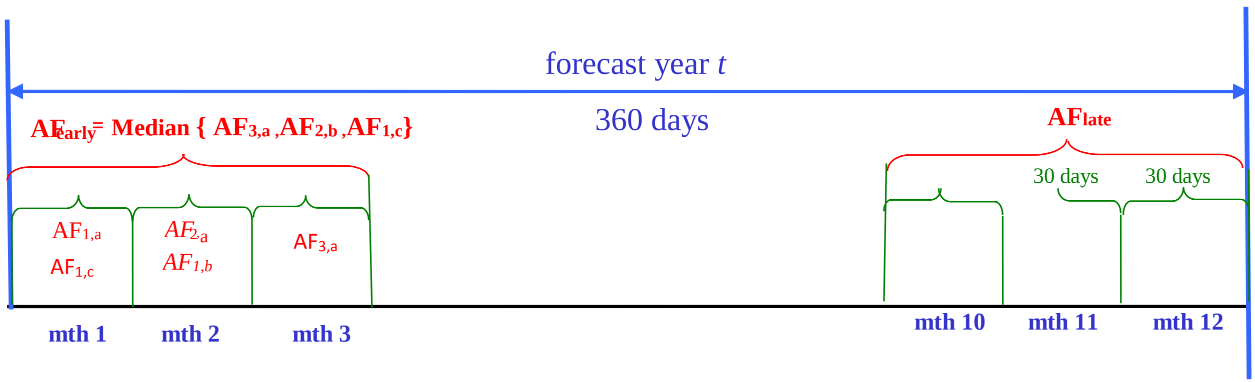

Figure 1.
Timeline – forecast year, forecast month, and consensus analyst forecast construction

Step 2: Identify the evidence of management forecast guidance

Prior studies use downward revisions in analyst forecasts as evidence for forecast guidance. However, downward revisions can also be caused by unexpected bad news that arises throughout the forecast year. In particular, analysts may revise their earnings forecasts downward to incorporate any unexpected firm-specific or economy-wide bad news that occurs during the year. This study uses the following regression model to isolate management guidance-induced forecast revisions from forecast revisions driven by economic or firm-specific news occurring during the year.

$$Rev_{it} = b_0 + b_1 CRET_{it} + \varepsilon_{it} \tag{1}$$

In this model, Rev_{it} is the change in analyst consensus forecasts from the beginning to the end of the year (i.e., $Rev_{it} = AF_{it}^{late} - AF_{it}^{early}$), and $CRET_{it}$ is the cumulative return during the year. The accumulation period starts from the first day of the forecast year and ends 20 days before the current year's earnings announcement. The cumulative return term ($CRET_{it}$) captures the impact of economy-wide and/or firm-specific news on analyst forecast revisions. This regression is estimated for each 2-digit SIC-code industry group in each year and the residuals (i.e., the estimate of ε_{it}) from this regression are used as the measure for the unexpected forecast revision ($UnExpRev_{it}$). This study classifies firm-years with unexpected downward revisions ($UnExpRev_{it} < 0$) as possible forecast guiders. Combining these two steps, forecast guiders are defined as the firm-years that are classified as possible guiders in both Step 1 and Step 2.

This study creates a matched non-guider sample based on industry, year, and forecast error to minimize sample differences in these aspects. Prior studies, such as Frankel and Lee (1998) and Easton and Sommers (2007), suggest that errors in analyst earnings forecasts reduce the accuracy of forecast-based estimates. Matching on forecast errors ensures that the observed difference in the accuracy of V between the guider and non-guider samples is not driven by differences in forecast errors. To construct the non-guider sample, for each guider, all firms that are in the same industry and year are selected from the group of firms that are not in the guider sample. Among these selected observations, the one with the closest forecast error to the guider is defined as the matched non-guider.

Intrinsic value measure

Ohlson (1995) develops the RIM to express firm value as a linear function of accounting book value, abnormal earnings and the other information about future abnormal earnings:

$$V_t = b_t + \alpha_1 x_t^a + \alpha_2 v_t \tag{2}$$

In this model, b_t is the accounting book value of shareholders' equity at time *t*, x_t is the earnings for the period from *t-1* to *t*, and x_t^a is abnormal earnings ($x_t^a = x_t - rb_{t-1}$). v_t is the other information variable, defined as the difference between the expectation of future abnormal earnings based on all information and the expectation of future abnormal earnings based only on the current abnormal earnings ($v_t = E_t[x_{t+1}^a]$ - ωx_t^a). The parameters α_1 and α_2 are computed as $\alpha_1 = \omega_t /(1 + r - \omega_t)$ and $\alpha_2 = (1 + r) /(1 + r - \omega_t)(1 + r - \gamma_t)$, where ω_t and γ_t are the first-order autoregressive coefficients for abnormal earnings and other information, estimated using the following pooled time-series cross-sectional regressions:

$$x_{t+1}^a = \omega x_t^a + v_t + u_{1,t+1} \tag{3}$$

$$v_{t+1} = \gamma v_t + u_{2,t+1} \tag{4}$$

In these regressions, $u_{1,t+1}$ and $u_{2,t+1}$ are the mean zero disturbance terms.

This study uses the consensus analyst earnings forecast at the end of the year (AF_t^{late}) to estimate the expectation of future abnormal earnings:

$$E_t[x_{t+1}^a] = AF_t^{late} - rb_t\,. \tag{5}$$

It then expresses the other information variable as

$$v_t = (AF_t^{late} - rb_t) - \omega_t x_t^a\,. \tag{6}$$

The forecast-based intrinsic value metric V is constructed for each firm at the end of each forecast year as follows:

$$V_t = b_t + \alpha_1 x_t^a + \alpha_2 (AF_t^{late} - rb_t - \omega x_t^a)\,. \tag{7}$$

Empirical analyses

The empirical analysis include explanation of contemporaneous stock prices as well as prediction of future returns through V/P ratios. These are explained below.

Explanation of contemporaneous stock prices. Prior studies (e.g., Frankel and Lee, 1998; Lee et al., 1999) examine the cross-sectional correlations between V and P to assess the ability of V to explain stock price. These studies find that analyst forecast-based V has higher correlations with stock price than other value metrics. Following prior studies, this study also employs a correlation analysis to assess the ability of V to explain stock price. If forecast guidance impairs the ability of V to predict firm value as hypothesized, V estimated using guided forecasts would have lower correlations with stock price than those estimated using non-guided forecasts.

To carry out the correlations test, for the guider and non-guider samples separately, this study calculates the cross-sectional Spearman correlation coefficients between V and P at the end of each year. This study then compares these annual correlation statistics between the two samples, expecting the correlations to be lower for the guiders than the non-guiders. To ensure that the correlation difference between the guiders and non-guiders is not due to sample differences in aspects other than forecast guidance, this study examines the conditional correlations between V and P, controlling for firm size, earnings performance, book-to-market ratio, and analyst forecast error. Specifically, for the guider and non-guider samples separately, this study computes the conditional correlations for each sample in the following steps. First, it estimates the following regressions:

$$P_{i,t} = c_1 BV_{i,t} + c_2 EPS_{i,t} + c_3 B/M_{i,t} + c_4 FE_{i,t} + e_{it} \tag{8}$$

$$V_{i,t} = c_1 BV_{i,t} + c_2 EPS_{i,t} + c_3 B/M_{i,t} + c_4 FE_{i,t} + v_{it} \tag{9}$$

In these regressions, BV_{it} is the accounting book value of shareholders' equity per share at the beginning of year *t*. EPS_{it} is earnings per share for year *t-1*. FE_{it} is analysts' consensus forecast for year *t*'s earnings measured at the end of year *t* prior to the earnings announcement; the residual $\hat{e}_{it}$ ($\hat{v}_{it}$) represents the part of $P_{i,t}$ ($V_{i,t}$) that cannot be explained by these control variables for firm size, earnings performance, B/M ratio, and forecast accuracy. The residuals $\hat{e}_{it}$ and $\hat{v}_{it}$ are then used to estimate the following regression:

$$\hat{e}_{it} = a + b\hat{v}_{it} + u_{it} \tag{10}$$

In this model, $\hat{b}$ captures the strength of the relation between V and P that is left unexplained after factoring out the effect of the control variables. This study then calculates the sample standard deviations of $\hat{e}_{it}$ and $\hat{v}_{it}$ and denote these standard deviations as $\hat{\sigma}_{\hat{e}}$ and $\hat{\sigma}_{\hat{v}}$ respectively. Finally, the conditional correlation between V and P is calculated as

$$\hat{\rho}_{\hat{e}\hat{v}} = \hat{b}\left(\frac{\hat{\sigma}_{\hat{v}}}{\hat{\sigma}_{\hat{e}}}\right) \tag{11}$$

This study compares the conditional correlations for the guider and non-guider samples, expecting the conditional correlations for the guiders to be lower than the conditional correlations for the non-guiders.

Prediction of future returns through V/P ratios. Better V estimates have greater ability to predict future returns through V/P ratios. Frankel and Lee (1998) and Dechow et al. (1999) find the 12-month cumulative returns to the V/P ratio portfolio strategy of buying high V/P ratio (under-valued) stocks and selling low V/P ratio (over-valued) stocks to be positive and significant. The returns prediction analysis compares the V/P ratio portfolio returns for forecast guiders and non-guiders over the 12 months following forecast guidance, expecting the portfolio returns to be greater for the non-guiders than for the guiders.

Firms report earnings in different months. To align the sample in calendar time, this study uses firms that report earnings in February as the sample in the returns analysis. At the end of each forecast year, the V/P ratio for each firm-year observation is computed using stock price at the end of the month. For the guiders and non-guiders separately, this study ranks firms by V/P ratios and assign these firms to quintiles. It then calculates the cumulative return for each quintile portfolio over the subsequent 12 months. The hedge portfolio return is computed as the difference in returns between the top and bottom V/P quintiles. This study compares the hedge portfolio returns for the guider and non-guider samples, expecting a higher return for the non-guider sample than for the guider sample.

One remaining concern is that the difference in the hedge portfolio returns for the guider and non-guider samples might be caused by their different risk profiles. To address this concern, this study uses the Fama and French (1993) three-factor model to control for risks and examine the risk-adjusted returns. To implement the test, for the guider and non-guider samples separately, firms are ranked by V/P ratios and partitioned into quintiles. This study then computes the average monthly return for each V/P quintile and calculates the monthly hedge portfolio return as the difference in returns between the top and bottom V/P quintiles (i.e., $Hret_t^G = Ret_t^{G,Q5} - Ret_t^{G,Q1}$, and $Hret_t^N = Ret_t^{N,Q5} - Ret_t^{N,Q1}$). This study then regresses the monthly hedge portfolio returns on the three monthly Fama and French risk factors and the momentum factor as follows:

$$Hret_t^G = \alpha_t^G + \beta_1 MktRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t^G \qquad (12)$$

$$Hret_t^N = \alpha_t^N + \beta_1 MktRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t^N \qquad (13)$$

In these regressions, α_t^G and α_t^N represent the risk-adjusted returns to the V/P ratio portfolio strategy for the guider and non-guider samples respectively. To examine the significance of the difference in the risk-adjusted returns between the two samples, this study takes the difference in the monthly hedge portfolio returns between the guider and non-guider samples ($Hret_t^{N-G} = Hret_t^N - Hret_t^G$) and regresses these monthly return differences on the monthly Fama and French (1993) risk factors and the momentum factor as follows:

$$Hret_t^{N-G} = \alpha_t^{N-G} + \beta_1 MktRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t^{N-G} \qquad (14)$$

The estimated intercept (α_t^{G-N}) summarizes the difference in returns to the V/P ratio portfolio strategy for the non-guider and guider samples after controlling for risk differences between the two samples.

Empirical Results

This section describes the data collection and sample statistics. Then, descriptive statistics are presented, follow by the empirical analyses.

Data collection and sample statistics

The sample consists of non-regulated and non-financial U.S. firms for the time period from 1986 to 2007. Following Richardson et al. (2004) and Matsumoto (2002), firms in the regulated and financial industries are excluded because their accounting rules differ from the accounting rules for firms in other industries. Thus, firms in the regulated and financial industries may therefore have different motives with respect to forecast guidance. The final sample consists of 8,324 guiders and 8,324 matched non-guiders[2].

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[2] To construct the sample, this study first obtains the forecasted and actual earnings-per-share (EPS) data from IBES History U.S. Edition tape (Actual File) through the Wharton Research Data System (WRDS). This study then matches the resulting sample to the Center for Research in Security Prices (CRSP) database and Compustat database, resulting in an initial sample of 11,494 firms and 80,570 firm-years. Firms in the financial and regulated industries, and firms without

Descriptive statistics

Table 1 reports the summary statistics on the variables used to construct the V metrics in each year of the sample period from 1986 to 2007. The control variables BV_{it}, EPS_{it}, B/M_{it}, and FE_{it} are as defined earlier. ω_t and γ_t are the first-order autoregressive coefficients for abnormal earnings and other information in year *t*. V is the intrinsic value metric estimated at the end of each year using BVPS, EPS, AF, ω, and γ. These annual statistics illustrate the stability of the key input variables over the sample period.

Table 1.
Summary statistics of model input variables

Year	Obs.	BVPS	ESP	AF	Omega	Gamma	V
1986	456	12.05	0.45	0.49	0.65	0.49	13.03
1987	624	11.74	0.59	0.68	0.64	0.39	12.52
1988	592	10.66	0.73	0.81	0.65	0.46	11.12
1989	624	9.63	0.60	0.65	0.65	0.46	9.65
1990	720	10.22	0.54	0.61	0.65	0.49	10.35
1991	476	9.45	0.30	0.40	0.63	0.50	9.71
1992	632	9.89	0.46	0.51	0.60	0.53	10.62
1993	746	8.89	0.45	0.48	0.61	0.49	9.16
1994	900	8.49	0.52	0.55	0.63	0.51	8.72
1995	968	8.50	0.57	0.60	0.63	0.46	8.49
1996	1076	8.61	0.58	0.60	0.67	0.46	8.48
1997	1030	8.33	0.52	0.53	0.68	0.44	8.56
1998	970	8.12	0.62	0.64	0.72	0.43	8.59
1999	804	8.55	0.65	0.65	0.73	0.39	8.56
2000	944	9.29	0.79	0.80	0.74	0.35	9.10
2001	668	8.47	0.47	0.48	0.75	0.32	8.39
2002	662	8.23	0.51	0.52	0.74	0.26	8.78
2003	720	8.83	0.46	0.46	0.71	0.17	8.39
2004	910	10.81	0.96	0.94	0.72	0.15	10.48
2005	1154	9.34	0.93	0.91	0.73	0.18	9.57
2006	904	9.64	1.08	1.08	0.74	0.14	9.85
2007	68	10.37	1.23	1.21	0.79	0.21	11.07
All years	16,648	9.46	0.64	0.66	0.68	0.38	9.69

Explanation of contemporaneous stock prices

The correlation test examines the unconditional and conditional correlations between V and P at the end of each year. Table 2 reports the annual unconditional correlation coefficients for the guiders and non-guiders and the difference in these statistics between the two samples. The last row of this panel reports the time-series means of the annual correlation statistics. As shown in the panel, the

necessary data are removed, reducing the sample to 5,548 firms and 31,763 firm-year observations. Out of these 31,736 firm years, 8,324 are classified as forecast guiders and these guiders are matched with 8,324 non-guiders.

correlation between stock price and intrinsic value metrics estimated using guided forecasts is 0.47 on average. It is lower than the correlation between stock price and intrinsic value metrics estimated using non-guided forecasts (0.58). This correlation difference of 0.11 is statistically significant at the 1% level (t=2.81).

Table 2
Annual cross-sectional Spearman correlations between V and P

Year	$Corr_t^N(V,P)$	$Corr_t^G(V,P)$	Difference
1986	0.72	0.59	0.13
1987	0.65	0.51	0.13
1988	0.70	0.68	0.01
1989	0.60	0.56	0.04
1990	0.61	0.52	0.09
1991	0.54	0.32	0.22
1992	0.64	0.58	0.07
1993	0.72	0.50	0.22
1994	0.62	0.38	0.24
1995	0.61	0.40	0.21
1996	0.62	0.54	0.08
1997	0.67	0.53	0.14
1998	0.58	0.21	0.38
1999	0.22	0.13	0.09
2000	0.38	0.32	0.07
2001	0.49	0.41	0.09
2002	0.46	0.46	0.00
2003	0.49	0.54	-0.05
2004	0.63	0.60	0.03
2005	0.61	0.60	0.01
2006	0.66	0.58	0.08
2007	0.50	0.43	0.07
All Years	0.58	0.47	0.11*** (t=2.81)

Table 3 reports the conditional correlation statistics between V and P, controlling for the effects of firm size (book value of equity), earnings performance (ESP), book-to-market (B/M) ratio, and forecast errors, one factor at a time. The last row of the panel reports the conditional correlation between V and P after controlling for these factors together. All statistics reported are the time-series means of the annual statistics.

Results in Table 3 show that the conditional correlations for the guider sample are significantly lower than the conditional correlations for the non-guider sample. This suggests that the difference in correlations between the two samples cannot be explained by their differences in firm size, earnings performance, B/M ratio, or forecast accuracy.

Table 3

Conditional Correlations

Conditional correlation (V, P)	N	G	N-G	t Value
Control for firm size (BV)	0.50	0.39	0.11***	2.48
Control for earnings performance (EPS)	0.42	0.31	0.11***	2.23
Control for book-to-market (B/M) ratio	0.64	0.53	0.11***	2.82
Control for forecast accuracy (FE)	0.58	0.47	0.11***	2.82
Control for size, EPS, B/M, FE	0.44	0.35	0.09***	2.06

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

In summary, results from the correlation analyses provide consistent evidence that V estimated using guided forecasts have less ability to explain contemporaneous stock price than V estimated using non-guided forecasts.

Prediction of future returns through V/P ratios

The returns prediction analysis examines the returns to the V/P ratio portfolio strategy for forecast guiders and non-guiders. Table 4 reports, for the guiders and non-guiders separately, the 12-month cumulative return to each V/P quintile portfolio and the hedge portfolio. In February of each year, for the guiders and non-guiders separately, observations are ranked by V/P ratios and partitioned into quintiles. Returns are accumulated for each quintile portfolio for the subsequent 12 months. Table 4 reports, for the guider and non-guider samples separately, the cumulative return to each V/P quintile portfolio (Q1 to Q5) and the hedged portfolio. The hedge portfolio return ($HRet_t$) is computed as the difference in returns between the top and bottom V/P quintiles (RetQ5-RetQ1). The last row of the table reports the difference in hedge portfolio returns between the non-guider and guider samples. T-statistics are based on the time-series standard errors of the annual portfolio returns.

Table 4:
Buy-and-hold returns to the V/P-ratio portfolio strategies (G vs. N)

V/P quintile portfolio returns	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	Q5-Q1 ($HRet_t$)
Non-guider (N)	0.10	0.14	0.11	0.14	0.21	0.12* (t=1.89)
Guider (G)	0.21	0.12	0.14	0.13	0.15	-0.06 (t=-0.98)
Difference (G-N)						0.18*** (t=3.01)

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

As shown in Table 4, over a 12-month interval, the average hedge portfolio return for the non-guider sample is 12%. With a t-statistic of 1.89, this return is significant at the 7% level.[3] This

[3] The V/P ratio portfolio returns to the non-guider sample is larger in magnitude (11.7% versus 7.1%), and slighter higher in statistical significance (t=1.89 versus t=1.77) than results reported in Dechow et al. Following Frankel and Lee (1998),

result provides some evidence that, in the absence of forecast guidance, the forecast-based V is a superior measure for firm value than stock price and can therefore predict future returns through V/P ratios. In contrast, the average hedge portfolio return for the guider sample is -6.0%, statistically insignificant (t=-0.98). This result suggests that when V is estimated using guided forecasts, V becomes a less accurate measure for firm value and can no longer predict future returns through V/P ratios. The difference in the hedge portfolio returns between the non-guider and guider samples is 18%. With a t-statistic of 3.01, this return difference is statistically significant at the 1% level. This suggests that V estimated using guided forecasts have less power to predict future returns through V/P ratios than those estimated using non-guided forecasts.

As a robustness check, this study uses the Fama and French three-factor model to control for risks and examine the risk-adjusted returns. Table 5 Panel A reports the risk-adjusted returns to the V/P ratio portfolio strategy for the guider and non-guider samples separately. For each sample (i.e., guiders and non-guiders), firms are ranked by V/P ratios and partitioned into quintiles. The average monthly return is computed for each V/P quintile. The monthly hedge portfolio return is defined to be the difference in the monthly returns between the top and bottom V/P quintiles. These monthly hedge portfolio returns are regressed on the three Fama and French risk factors and the momentum factor to obtain the risk adjusted returns. To examine the risk-adjusted return differences between the guider and non-guider samples, this study takes the difference in the monthly hedge returns between the two samples and regress these monthly return differences on the monthly Fama and French risk factors and the momentum factor. The estimated intercept term from the following regression model captures the risk-adjusted return differences between the guiders and non-guiders. Table 5 Panel B reports the difference in risk-adjusted returns between guiders and non-guiders.

As shown in Panel A, the risk-adjusted return for the non-guider sample ($\alpha_{m,t}^{N}$) is 1.0%, statistically significant at the 1% level. In contrast, the risk-adjusted return to the guider sample ($\alpha_{m,t}^{G}$) is -0.6%, statistically significant at the 10% level. The difference in the risk-adjusted returns between the two samples, as shown in Panel B, is 1.6%, statistically significant at the 1% level. These results suggest that, after controlling for risks, the V/P ratio portfolio strategy for the non-guider sample is still able to earn a significantly higher return than that for the guider sample. Overall, the returns prediction results suggest that management forecast guidance tends to reduce the ability of forecast-based V to predict future returns through V/P ratios.

this study also assesses the statistical significance of the returns using Monte Carlo simulations; results from this analysis show that the V/P ratio portfolio returns to the non-guider sample are statistically significant at the 1% level.

Table 5
Risk-adjusted returns to the V/P ratio portfolio strategies (G vs. N)

Panel A: Risk-adjusted returns to the V/P ratio portfolio strategy for G and N separately

Non-Guider (N)

Variable	Parameter Estimate	Standard Deviation	T value
Intercept ($\alpha^{N}_{m,t}$)	0.010***	0.004	2.59
Market – Risk free rate	0.989***	0.096	10.31
Small – Big	0.992***	0.113	8.77
High – Low	0.451***	0.138	3.26
Momentum	-0.744***	0.081	-9.17

Guider (G)

Variable	Parameter Estimate	Standard Deviation	T value
Intercept ($\alpha^{G}_{m,t}$)	-0.006*	0.004	-1.66
Market – Risk free rate	0.092	0.093	0.99
Small – Big	0.240**	0.109	2.19
High – Low	1.384***	0.134	10.37
Momentum	-0.509***	0.078	-6.49

Panel B: Risk-adjusted return difference between guiders and non-guiders

$$Hret^{N}_{t} - Hret^{G}_{t} = \alpha^{N=G}_{t} + \beta_1 MktRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon^{N-G}_{i}$$

Variable	Parameter Estimate	Standard Deviation	T value
Intercept ($\alpha^{N-G}_{m,t}$)	0.016***	0.006	2.90
Market – Risk Free	-0.290**	0.145	-2.00
Small – Big	-0.388***	0.171	-2.27
High – Low	-0.585***	0.209	-2.80
Momentum	-0.189	0.122	-1.55

Conclusion

Prior valuation studies provide consistent evidence for the usefulness of analyst forecasts and the superior ability of forecast-based valuation models to predict firm value. This study shows that analyst forecasts are less useful than previously documented because of the increased management forecast guidance. In particular, this study examines the impact of management forecast guidance on the usefulness of analyst forecasts in firm valuation by empirically comparing the performance of intrinsic value metrics estimated using guided versus non-guided forecasts to explain stock price and predicting future returns through V/P ratios.

The results show that V estimated using guided forecasts have significantly lower correlations with P than those estimated using non-guided forecasts. The lower correlations cannot be explained by factors such as firm size, earnings performance, B/M ratio, or forecast accuracy. In addition, the returns to the V/P ratio portfolio strategy for the guider sample are significantly lower than those for the non-guider sample, and this return difference cannot be explained by the risk differences between the two samples. Together, these results suggest that management forecast guidance tends to reduce the ability of forecast-based V to track stock price and predict future returns through V/P ratios. This study therefore concludes that forecast guidance reduces the usefulness of analyst forecasts in firm valuation.

This study contributes to the financial analyst and expectations management literature by documenting the impact of management forecast guidance on the usefulness of analyst forecast in firm valuation. It extends the valuation literature by conditioning model performance on the quality of model inputs and documenting the adverse impact of management forecast guidance on valuation model performance. Results from this study raise awareness among researchers, practitioners, and investors about the pitfalls of taking analyst forecasts at face value and using them directly in firm valuation.

This study has one major limitation. In particular, this study examines only one input to the RIM valuation model (i.e., analyst earnings forecast), while holding other model inputs (i.e., book value of equity and earnings) constant. Since firm managers can manipulate other model inputs, this study suggest future research to further investigate the impact of management manipulation of other model inputs on the performance of earnings-based valuation models.

References

Abarbanell, J., & Bernard, V. (1991). Tests of analysts' overreaction/undereaction to earnings information as an explanation for anomalous stock price behavior. *Journal of Finance, 47*, 1181-1207.

Athanasakou, V., Strong, N., & Walker, M. (2009). Earnings management or forecast guidance to meet analyst expectations? *Accounting and Business Research, 39* (1), 3-35.

Bartov, E., Givoly, D., & Hayn, C. (2002). The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics, 33,* 173–204.

Bartov, E., & Cohen, D.A. (2009). The "numbers game" in the pre- and post-Sarbanes-Oxley eras. *Journal of Accounting, Auditing and Finance, 24, 505-534*.

Brown, L., & Higgins, H.N. (2005). Managers' forecast guidance of analysts: International evidence. *Journal of Accounting and Public Policy, 24,* 280-299.

Brown, R.M., & Pinello, A.S. (2007). To what extent does the financial reporting process curb earnings surprise games? *Journal of Accounting Research, 45*(5), 947-981.

Burgstahler, D., & Eames, M. (2006). Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises. *Journal of Business Finance and Accounting, 33*, 633-652.

Coller, M., & Yohn, T.L. (1997). Management forecasts and information asymmetry: An examination of bid-ask spreads. *Journal of Accounting Research, 35*(2), 181-191.

Dechow, P.M., Hutton, A.P., & Sloan, R.G. (1999). An empirical assessment of the residual income valuation model. *Journal of Accounting & Economics, 26*, 1–34.

Easton, P., & Sommers, G. (2007). Effect of analysts' optimism on estimates of the expected eate of return implied by earnings forecasts. *Journal of Accounting Research, 45*, 983-1015

Fama, E., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33: 3.

Frankel, R., & Lee, C.M.C. (1998). Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and Economics, 25*, 283–319.

Gaio, C., & Raposo, C. C. (2014). Corporate governance and earnings quality – international evidence. *Journal of Accounting and Finance*: 14 (3), 52-74.

Graham, R. J., Harvey, R. C, & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics, 40*, 3-73.

Hutton, A., Miller, G.S., & Skinner, D. (2003). The role of supplementary statements with management earnings forecasts. *Journal of Accounting Research, 41*, 867-890.

Koh, K., Matsumoto, D.A., & Rajgopal, S. (2008). Meeting or beating analyst expectations in the post-scandals world: Changes in stock market rewards and managerial actions. *Contemporary Accounting Research, 25* (4), 1067-1098.

Kasznik, R., & Lev, B. (1995). To warn or not to warn: management disclosures in the face of an earnings surprise. *The Accounting Review, 70* (1), 113-134.

Kasznik, R., & McNichols, M. (2002). Does meeting earnings expectations matter? Evidence from analyst forecasts revisions and share prices. *Journal of Accounting Research, 40*, 727–759.

Kross, W.J., Ro, B.R., & Suk, I. (2011). Consistency in meeting or beating earnings expectations and management earnings forecasts. *Journal of Accounting and Economics, 51*, 37-57.

Lansford, B., Lev, B., & Tucker, W. J. (2013). Causes and consequences of disaggregating earnings guidance. *Journal of Business, Finance and Accounting, 40*: 26-54.

Lang, M.H., & Lundholm, R.J. (1996). Corporate disclosure policy and analyst behaviour. *The Accounting Review, 71* (4), 467-492.

Lee, C.M.C., Myers, J., & Swaminathan, B. (1999). What is the intrinsic value of the Dow? *The Journal of Finance, 54*, 1693–1741.

Matsumoto, D. (2002). Management's incentive to avoid negative earnings surprises. *The Accounting Review, 77*, 483–514.

Ohlson, J.A. (1995). Earnings, book values, and dividends in equity valuation. *Contemporary Accounting* Research 11, 661–687.

Richardson, S., Teoh, S., & Wysocki, P. (2004). The walk-down to beatable analyst forecasts: the role of equity issuances and insider trading incentives. *Contemporary Accounting Research 21*, 885–924.

Sohn, B.C. (2012). Analyst forecast, accounting conservatism and the related valuation implications. *Accounting and Finance* 52, 311-341.

Xie, Y. (2011). The market effects of breaking a string of meeting or beating analysts' expectations: downward revision of future cash flows or increase in cost of equity capital*? Journal of Business Finance and Accounting 38* (1)&(2), 95-11.

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