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Why don't Analysts use their Earnings Forecasts in Generating Stock Recommendations?*

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Abstract

While a large body of literature has examined analysts' earnings forecasts or stock recommendations in isolation, there is little research on the effectiveness with which analysts translate their earnings forecasts into recommendations (referred to as translational effectiveness). This study provides a comprehensive analysis of the determinants of analysts' translational effectiveness, including the investment banking pressure considered in prior research and four new factors (i.e. insider trading, trading commissions, institutional ownership, and investor sentiment). Consistent with prior research, we find that the influence of investment banking on translational effectiveness was reduced in the period subsequent to the 2002/2003 regulatory changes. However, the effect of insider trading, institutional ownership, and investor sentiment on translational effectiveness remains as significant or becomes even stronger. In addition, the combined influence of these four new factors on translational effectiveness is equally as important as the influence of investment banking pressure.

Keywords: Analyst, Recommendation, Earnings Forecast

JEL codes: G14; M41

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为何分析师不使用他们的盈利预测来产生股票评级？[*]

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摘要

尽管大量文献都孤立地分析了分析师的收益预测或股票评级，关于分析师将其盈利预测转化为股票评级的有效性的研究很少（称为分析师转化效率）。本文对分析师转化效率的决定因素进行了全面分析，包括先前研究中考虑的投资银行压力和四个新因素（即内幕交易、交易佣金、机构投资者和投资者情绪）。与先前的研究一致，在2002/2003 年法规变更之后的一段时间内，投资银行业务对分析师转化效率的影响有所降低。但是，内幕交易、机构投资者和投资者情绪对分析师转化效率的影响仍然很重要，甚至变得更强。此外，这四个新因素对分析师转化效率的综合影响与投资银行压力的影响同等重要。

关键词：分析师、股票评级、盈利预测

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I. Introduction

Financial analysts play a significant role in the functioning of capital markets around the world. As information intermediaries, one of the responsibilities of analysts is to help investors process complex financial information in order to produce timely and accurate earnings forecasts. However, earnings forecasts are usually considered not as a final product but as an input in generating profitable stock recommendations (Brown, 1993; Schipper, 1991). Analysts' stock recommendations are widely followed by equity investors, especially those who do not have the time or necessary skills to process financial information (including earnings forecasts) to form an independent assessment of a stock's value (see, for example, Malmendier and Shanthikumar, 2007; Mikhail *et al.*, 2007). Hence, it is crucial to understand not only how well analysts forecast earnings but also how well they translate their earnings forecasts into recommendations.

Although there is a large body of literature that studies analysts' earnings forecasts or stock recommendations in isolation,[5] as noted by Bradshaw (2009), there is only limited research on the effectiveness with which analysts translate their earnings forecasts into recommendations, hereinafter referred to as translational effectiveness. Bradshaw's (2004) study was the first to show that analysts' consensus recommendations do not completely incorporate the information in the consensus earnings forecasts. He finds that analysts' consensus recommendations can be better explained by heuristic valuation models (e.g. the price-earnings-to-growth or PEG model) than by sophisticated residual income valuation models.[6] In addition, a buy-and-hold investment strategy based on firm value estimated using analysts' earnings forecasts and residual income valuation models outperform a buy-and-hold investment strategy based on analysts' consensus recommendations over a one-year horizon following the consensus recommendation announcement.

Inspired by Bradshaw (2004), researchers have investigated the factors that reduce analysts' translational effectiveness. Barniv *et al.* (2009), Chen and Chen (2009), and Ertimur *et al.* (2007) all examine the influence of investment banking on analysts' translational effectiveness before and after the 2002/2003 regulatory changes that were designed to reduce the influence of investment banking on analyst research. Despite the difference in methodologies, all three studies conclude that the 2002/2003 regulatory changes have reduced the negative influence of investment banking on analysts' translational effectiveness.

However, investment banking is not the only determinant of analysts' translational effectiveness. In addition, with the substantially reduced influence of investment banking pressure in the post-regulatory-change period, it has become increasingly important to

[5] See Brown (1993), Kothari (2001), and Ramnath *et al.* (2008) for reviews of this literature.

[6] Barniv *et al.* (2010) extend Bradshaw's (2004) findings to an international setting. They find that analysts do not appear to use their own forecasts in producing recommendations, especially in countries with higher investor participation.

identify and understand the effects of other forces on analysts' translational effectiveness. The objective of this study is to conduct a comprehensive analysis of the determinants of analysts' translational effectiveness over the period 1993 to 2005. As we explain in Section 3.3, analysts' translational effectiveness could suffer due to either conflicts of interest or behavioural biases or both. Besides investment banking pressure, we consider three alternative sources of conflicts of interest, namely, insider trading, trading commissions, and institutional ownership. We also use the most comprehensive measure of investor sentiment developed by Baker and Wurgler (2006) to test the influence of behavioural biases on translational effectiveness.

The extant analyst literature has considered the effect of our proposed factors on either earnings forecasts or recommendations. Bradshaw *et al.* (2006), Dugar and Nathan (1995), and Lin and McNichols (1998) have examined the influence of investment banking on recommendations and earnings forecasts. Chen and Chen (2009), Cowen *et al.* (2006), Irvine (2004), and Jackson (2005) have studied the relation between trading commissions and biases in analysts' earnings forecasts and recommendations. Ke and Yu (2006) and Richardson *et al.* (2004) have considered the influence of insider trading on analysts' earnings forecast biases. Ljungqvist *et al.* (2007) have examined the relation between institutional ownership and analysts' earnings forecast accuracy and recommendation optimism.

However, these studies do not examine the effect of these factors on analysts' translational effectiveness. A common methodology in the analyst literature is to regress analysts' recommendations on firm or analyst characteristics. For example, Ljungqvist *et al.* (2007) regress analysts' relative stock recommendations on institutional ownership to assess the influence of institutional investors on recommendation optimism. While appropriate for Ljungqvist *et al.*'s research question, this regression does not test the influence of institutional ownership on translational effectiveness, which requires an examination of the association between analysts' earnings forecasts and recommendations as a function of institutional ownership. Our study is the first to analyse the influence of the above four new factors on analysts' translational effectiveness, while Barniv *et al.* (2009), Chen and Chen (2009), and Ertimur *et al.* (2008) are the first studies that examine the effect of investment banking pressure on translational effectiveness.

We use each analyst's short-term and long-term earnings forecasts issued on the same day as his or her recommendation to construct an independent estimate of firm value relative to the prevailing stock price prior to the recommendation announcement (denoted *V/P*). Consistent with Bradshaw (2004), we find that *V/P* outperforms recommendations in predicting future abnormal stock returns over a one-year horizon beginning on the trading day prior to the recommendation announcement date, suggesting that analysts do not fully translate their earnings forecasts into recommendations. We also confirm the prior finding that investment banking pressure reduces analysts' translational effectiveness in the period before the 2002/2003 regulatory changes but not in the period after the changes.

More importantly, however, we find that all four new factors we propose have a significant impact on analysts' translational effectiveness in the sample period of 1993 to 2005. Specifically, analysts' translational effectiveness is lower when they follow firms with heavier insider selling or higher institutional ownership, when their brokerage houses rely more on trading commissions, or in the periods with more extreme investment sentiment. Furthermore, we find that the combined economic significance of the four new factors on translational effectiveness is equally as large as (if not greater than) the economic significance of investment banking pressure.

We further test the effect of the four new factors on translational effectiveness before and after the 2002/2003 regulatory changes. We find that trading commissions reduce analysts' translational effectiveness, but only in the period before the regulatory changes. However, the influence of insider trading, institutional ownership, and investor sentiment on analysts' translational effectiveness remains or becomes even stronger in the period after the regulatory changes.

The primary contribution of our study is to identify four new factors that affect analysts' translational effectiveness. Our findings are important for two reasons. First, there appears to be a presumption in the analyst literature and popular press that investment banking pressure is the primary culprit for biased analyst research.[7] We show that there are factors that are equally as important as investment banking pressure in influencing analysts' translational effectiveness but have not received as much attention from investors, researchers, and regulators. Second, with the reduced influence of investment banking pressure in the post-regulatory-change period, one may expect less biased analyst research. However, our results suggest there are factors other than investment banking pressure that influence analysts' translational effectiveness and thus investors should remain cautious in interpreting analysts' recommendations in the post-regulatory-change period.

The rest of the paper is organised as follows. Section II describes the sample selection procedures. Section III presents the research design, while Section IV reports descriptive statistics and test results. Section V concludes the paper.

II. The Sample

As the IBES initiated recommendation coverage in 1993, our sample includes all the stock recommendations available in the IBES over the 1993-2005 period that satisfy the following sample restrictions.[8] First, we require the annual earnings announcement date to

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7 Bradshaw (2011) and Cowen *et al.* (2006) have a similar observation.

8 Our sample ends in 2005 because we only have data on brokerage firm types (which are required for defining *BOOKRUNNER* and *SYNDICATE*) for the period 1980 to 2002. However, our sample period length should be sufficient for testing our research question.

occur no later than 180 days after the fiscal year end date to avoid complications associated with late earnings announcements. Second, we require each analyst in the IBES to disclose both the stock recommendation and one-year-ahead and two-year-ahead earnings forecasts that are issued on the *same date*. This restriction ensures that any identified discrepancy between an analyst's recommendation and *V/P* can be more unambiguously attributed to the analyst's failure to incorporate his or her earnings forecasts into recommendations rather than to a mismatch between the analyst's recommendation and the earnings forecasts he or she considers when generating that recommendation.[9] To avoid a further reduction in sample size, we do not require non-missing long-term earnings growth forecasts. Instead, we follow Frankel and Lee (1998) by replacing the missing long-term earnings growth forecasts with the estimates based on the one-year-ahead and two-year-ahead earnings forecasts (see Section 3.1). We obtain a total of 395,465 stock recommendation observations before imposing the above two sample restrictions. We lose approximately 16% and 54% of the total observations due to restrictions 1 and 2, respectively, resulting in a sample of 116,985 recommendations.[10] Due to missing data on other variables discussed later, the final sample used in later regression analysis is further reduced to 84,303 recommendation observations issued by 7,240 unique analysts for 5,780 unique stocks.

III. Research Design

3.1 The Valuation Model

Our research question requires an independent estimate of a stock's intrinsic value that fully incorporates the information in analysts' earnings forecasts. Following Frankel and Lee (1998, equation 3.3) and Ali *et al.* (2003), we use the following residual income valuation model to compute an independent estimate of a stock's intrinsic value per share at the time of stock recommendation *s* (denoted *V*):

$$V = B_t + \frac{(FROE_t - r_e)}{1+r_e} B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)^2} B_{t+1} + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2 r_e} B_{t+2} \tag{1}$$

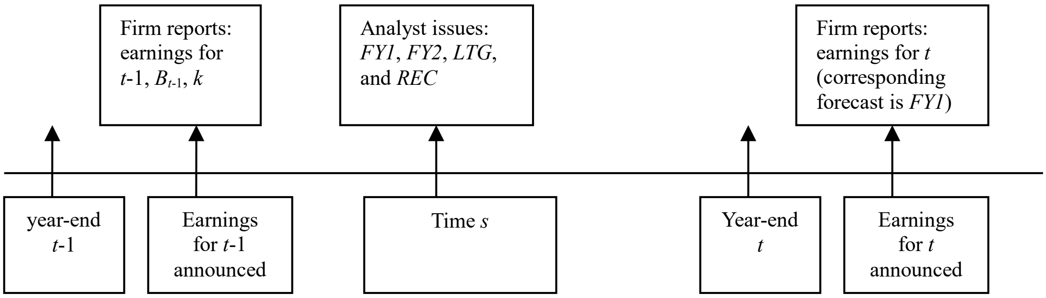
See Appendix A for definitions of the terms included in model (1). Figure 1 shows a

[9] Ljungqvist *et al.* (2009) find evidence of selective removal of analyst names from historic buy recommendations ("anonymisations") in the IBES that are *ex post* inaccurate. Because our sample selection procedures require non-missing analyst identification, anonymised recommendations are removed from our final sample. This sample selection bias will likely reduce the number of inconsistent stock recommendations in our sample and thus our ability to find the cross-sectional determinants of analysts' translational effectiveness.

[10] Conversations with IBES representatives suggest that the reason for the majority of the lost observations in restriction 2 is that analysts did not include updated earnings forecasts when submitting their recommendations. The final sample size does not change significantly if we relax restriction 2 by including earnings forecasts issued within 30 days ending on the recommendation date.

timeline of the key inputs used in our valuation model. Following prior research, we delete financial companies and observations that have *FROE* or k greater than 100% or a negative book value of shareholders’ equity. Because analyst recommendations are often leaked out one day prior to the disclosed recommendation announcement date, *V/P* is defined as V over the stock price two trading days prior to the recommendation date.[11]

Figure 1 A Timeline of the Key Inputs Used in the Intrinsic Value Calculation



Notes: The symbol t refers to fiscal year t. B is the book value of common equity. *FY1* and *FY2* are respectively one-year-ahead and two-year-ahead earnings forecasts issued at time s.

Valuation model (1) is a three-period Ohlson (1995) model assuming that the forecasted residual income in year t+2 continues in perpetuity. Consistent with Frankel and Lee (1998), our valuation model does not consider earnings forecasts longer than two years ahead because analysts do not always issue such longer horizon forecasts. In addition, analysts’ earnings forecast accuracy diminishes quickly with the forecast horizon, and thus forecasting errors are compounded in longer expansions of the Ohlson model.[12]

It is important to remember that the construct that V intends to capture is an independent estimate of a stock’s intrinsic value that reflects an analyst’s information in earnings forecasts. V is not a proxy for the *analyst’s* estimate of a stock’s intrinsic value. The analyst’s estimate of a stock’s intrinsic value is likely different from V because Bradshaw (2004) and Asquith *et al.* (2005) show that analysts often use heuristic valuation models, such as the price-earnings-to-growth (PEG) model, rather than more sophisticated residual income valuation models in firm valuation and in generating stock recommendations. Thus, even if available, an analyst’s estimate of a stock’s intrinsic value to stock price is inappropriate for our research question because it is less likely to capture the analyst’s earnings forecasts as well as *V/P*.

[11] Irvine *et al.* (2007) find that analysts’ stock recommendations could be leaked to favoured clients as early as five trading days before the disclosed recommendation announcement date. All of our inferences are robust to using the stock price five trading days prior to the recommendation announcement date to compute *V/P*.

[12] Prior research (e.g. Bradshaw, 2004; Frankel and Lee, 1998) demonstrates that the future abnormal stock return predictability of *V/P* is robust to alternative specifications of the residual income valuation model.

To illustrate, we use the future abnormal returns over a 12-month horizon that starts from the trading day prior to the recommendation announcement to compare the differential ability of the PEG model commonly used by analysts versus the residual income valuation model (1) in capturing the information in analysts' earnings forecasts. To be consistent with *V/P*, *V/P* based on the PEG model (denoted *V_PEG/P*) is defined as one-year-ahead earnings forecast multiplied by the long-term growth forecast divided by the stock price *P* (i.e. the inverse of the PEG model). The results are similar if the one-year-ahead earnings forecast is replaced by the two-year-ahead earnings forecast. Consistent with the calculation of *V/P*, we replace missing long-term growth forecasts with the growth rates implied from the one-year-ahead and two-year-ahead earnings forecasts. The Spearman correlation between *V/P* and *V_PEG/P* is only 0.077 ($p<0.001$). We find that the abnormal return is significantly negative (positive) for the portfolio of stocks in the top (bottom) quartile of *V_PEG/P*, while it is significantly positive (negative) for the portfolio of stocks in the top (bottom) quartile of *V/P* (untabulated). This evidence suggests that *V/P* does a much better job than *V_PEG/P* in capturing the information in analysts' earnings forecasts.[13]

It is also useful to point out some important features of *V* that may affect the interpretation of our subsequent results. First, since our objective is to examine whether analysts fully translate their earnings forecasts into recommendations, *V* deliberately excludes analysts' non-earnings information (e.g. short-term return momentum), which is usually unobservable but may be used by analysts to generate their recommendations. Second, even if non-earnings information is immaterial, our intrinsic value estimate may not be good due to either a bad model specification or bad inputs. It is possible that the residual income valuation model (1) does not fit all firms. In addition, the earnings generated from a firm's accounting system may not adequately capture firm value. Alternatively, the earnings quality is sound but analysts' earnings forecasts are low in quality. We will discuss how such measurement problems may affect the interpretation of our empirical results in sections 3.2 and 3.3.

3.2 Return Profitability of Recommendations versus *V/P*

Before analysing the determinants of analysts' translational effectiveness, we first establish that analysts' recommendations do not fully incorporate the information in their earnings forecasts summarised in *V/P*. To demonstrate this effect, we examine the abnormal returns of the following four types of recommendations: (1) a strong buy or buy with a *V/P* in the bottom quartile of the whole sample (denoted inconsistent buy); (2) a strong buy or buy with a *V/P* in the top quartile of the whole sample (denoted consistent buy); (3) a strong

[13] If we follow Bradshaw (2004) by deleting the observations with missing long-term earnings growth forecasts, the Spearman correlation between *V/P* and *V_PEG/P* is increased to 0.50, comparable to the 0.47 correlation reported in Bradshaw (2004, Table 3). In addition, *V/P* continues to outperform *V_PEG/P* in future abnormal returns for this restricted sample.

sell, sell, or hold with a *V/P* in the top quartile of the sample (denoted inconsistent sell); (4) a strong sell, sell, or hold with a *V/P* in the bottom quartile of the whole sample (denoted consistent sell). We group together holds with strong sells and sells because analysts issue very few sell recommendations and a hold recommendation is often interpreted as a sell.[14] As new information in analysts' earnings forecasts and recommendations is partially reflected in stock prices at the recommendation announcement date (Womack, 1996), the return window begins on the trading day prior to the recommendation announcement date. Because analysts' recommendations typically cover a 12-month forecast horizon, the return window ends either 12 months after the return window starting date or two days before the next recommendation issued by the same analyst, whichever comes first.[15]

To avoid the cross-sectional dependence of long-window stock returns (Bernard, 1987), we follow Barber *et al.* (2001) by constructing daily calendar time portfolios for each of the four types of stock recommendations. A stock is included in the daily portfolio if an analyst has issued a stock recommendation in the prior 12 months (shorter if the time gap between two recommendations issued by the same analyst is less than 12 months). If multiple analysts issue the same type of recommendation (e.g. strong buy or buy) on the same stock on the same day, the stock will be included multiple times in the daily portfolio. For each daily portfolio, we compute a value weighted mean raw return based on the market capitalisation of the stock at the close of the previous trading day. Then, we compound the value weighted daily raw returns in each month to derive a buy-and-hold monthly return (see Barber *et al.* (2001) for a detailed description of the method). The profitability of a particular type of stock recommendation is determined by the alpha from the time-series Fama-French four-factor model (i.e. the Fama and French three-factor model augmented with the Carhart (1997) momentum factor) over our sample period (1/1/1994–12/31/2005, a total of 144 months).

We use the abnormal stock returns on *inconsistent buys* and *inconsistent sells* to assess analysts' translational effectiveness. A negative abnormal return on inconsistent buys and a positive abnormal return on inconsistent sells would unambiguously indicate that analysts' stock recommendations have not fully incorporated their earnings forecasts (i.e. *V/P*). However, if the abnormal return on inconsistent buys (sells) is positive (negative), we cannot conclude that stock recommendations have fully incorporated their earnings forecasts. This is because stock recommendations could contain more than the earnings forecast information and thus even if *V/P* is not fully incorporated into stock recommendations, the abnormal stock return on inconsistent buys (sells) could be still positive (negative).

Similarly, a positive (negative) abnormal return on *consistent buys* (*consistent sells*)

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[14] Inference is qualitatively the same if the hold recommendations are excluded from the sell category.

[15] Bradshaw (2004) starts his one-year abnormal return calculation on the 15th day of the month subsequent to the consensus recommendation date, but as we show later, both he and this study reach the same conclusion that recommendations do not fully reflect analysts' earnings forecasts.

does not allow us to unambiguously infer whether analysts' recommendations have fully incorporated the *V/P* information. Although the positive (negative) abnormal return on consistent buys (consistent sells) would suggest that both analysts' recommendations and *V/P* capture firm value in the same direction, those abnormal returns do not indicate the extent to which analysts' stock recommendations reflect the *V/P* information. Nevertheless, we report the abnormal return results for all four types of recommendations for the sake of completeness.

As noted in Section 3.1, *V/P* omits non-earnings information and may measure a firm's intrinsic value with errors due to either a bad model or bad inputs. Because analysts are not constrained from using non-earnings information, using a better valuation model, or filtering out the noise in the bad inputs, their recommendations should be less affected by such measurement problems. Therefore, *V/P*'s measurement errors should bias against finding a negative (positive) abnormal return on inconsistent buys (inconsistent sells).

3.3 Determinants of Analysts' Translational Effectiveness

We use the following regression model to analyse the factors that affect analysts' translational effectiveness:

$$REC_{ijt} = a + b(V/P)_{ijt} + cZ_{ijt} + d(V/P)_{ijt} \times Z_{ijt} + \varepsilon_{ijt}\,, \tag{2}$$

where

i = stock index,

j = analyst index,

t = time index,

REC = analyst's stock recommendation that ranges from 5 (strong buy) to 1 (strong sell),

V/P = the ratio of a stock's intrinsic value to the stock price two trading days prior to the recommendation announcement date (see Section 3.1),[16] and

Z = a vector of analyst or firm specific attributes defined in Appendix B.

The dependent variable is a stock recommendation. The key independent variable is *V/P*, an independent measure of a firm's intrinsic value to stock price. Recall that *V* is not an analyst's estimate of the intrinsic value. As a higher (lower) *V/P* implies a higher (lower) future abnormal return, *V/P* is expected to be positively associated with *REC* in the absence of any biases. The primary interest of model (2) is to examine the factors *Z* that affect the relation between *V/P* and *REC* or translational effectiveness. As noted in the Introduction, our model (2) is fundamentally different from the typical unconditional regression of *REC*

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[16] Because stock recommendations are discrete while earnings forecasts are continuous, Francis and Soffer (1997) indicate that even if stock recommendations efficiently incorporate analysts' earnings forecasts, earnings forecasts should be incrementally informative relative to stock recommendations as a predictor of future stock returns. We have checked that our results are robust to using the quartile ranking of *V/P*.

on Z used in previous analyst studies.

Below, we discuss the factors Z that determine analysts' translational effectiveness.[17] We classify the factors Z into three broad categories: conflicts of interest (Section 3.3.1), investment sentiment (Section 3.3.2), and control variables (Section 3.3.3). The effect of conflicts of interest reflects analysts' conscious decision to distort translational effectiveness, while the effect of investor sentiment represents an unconscious error in analysts' translational effectiveness. Note that the effects of conflicts of interest and investor sentiment are not necessarily mutually exclusive and could exist in the same analyst.

3.3.1 Conflicts of interest

One important factor that reduces analysts' translational effectiveness is conflicts of interest (e.g. the well-known investment banking pressure). Although analysts facing conflicts of interest could be pressured to bias both earnings forecasts and recommendations, they have incentives to bias recommendations to a greater extent for two reasons. First, as recommendations represent a more comprehensive and direct view about a firm's value, analysts should face greater pressure from either firm managers or other interested parties (e.g. institutional investors, as discussed below) to issue biased recommendations than to issue biased earnings forecasts. Second, earnings forecasts can be easily verified against realised earnings, while biases in recommendations are much harder to detect due to the absence of an appropriate benchmark. As a result, analysts are less likely to be held responsible for issuing biased recommendations than they are for issuing biased earnings forecasts. Therefore, we predict analysts' translational effectiveness to decrease with their conflicts of interest. For the remaining discussion in this subsection, we will take this prediction as given and introduce specific examples of the conflicts of interest that may bias analysts' recommendations more relative to their earnings forecasts.

Analysts' conflicts of interest could arise from many sources. One source of conflicts of interest is the investment banking pressure examined in prior research (see, for example, Barniv *et al.*, 2009; Chen and Chen, 2009; Ertimur *et al.*, 2007). We use several proxies to capture different aspects of the investment banking influence. Following Ke and Yu (2006), we use *BOOKRUNNER* and *SYNDICATE* to assess the difference in translational effectiveness between analysts employed by investment banks and analysts employed by other brokerage firms. To the extent that investment bank analysts face a greater pressure to distort research reports, we expect the coefficients on *V/P×BOOKRUNNER* and *V/P×SYNDICATE* to be negative. Following Bradshaw *et al.* (2006), we also use

[17] An alternative regression setup to model (2) is to regress an indicator variable that equals one for inconsistent buy or sell recommendations (as defined in Section 3.2) and zero for consistent buy or sell recommendations on Z. Inferences from this alternative Probit regression are similar to those from model (2) except that the coefficients on *BOOKRUNNER*, *SYNDICATE*, and *INSIDERSELL* are positive but insignificant at the two-tailed 10% level. We prefer model (2) because it allows the inclusion of all the recommendations and is less restrictive.

EQUITYISSUE and *DEBTISSUE* to directly capture the influence of equity and debt financing on analysts' translational effectiveness. Bradshaw *et al.* find that the degree of analysts' stock recommendation optimism increases with a firm's equity financing but not with a firm's debt financing. Thus, we expect the coefficient on *V/P*×*EQUITYISSUE* to be negative. Although Bradshaw *et al.*'s finding suggests that *DEBTISSUE* will not have a material effect on analysts' translational effectiveness, we include both *EQUITYISSUE* and *DEBTISSUE* to be consistent with Bradshaw *et al.* (2006). As shown in prior research, the negative effect of investment banking pressure on translational effectiveness is expected to be stronger in the pre 2002/2003 regulatory change period.

In addition to the investment banking pressure, we consider three new sources of conflicts of interest that may reduce analysts' translational effectiveness. First, we consider the influence of insider selling over the calendar year prior to the recommendation year (*INSIDERSELL*). While insiders have an incentive to trade on their private information, Huddart *et al.* (2007) show that insiders prefer to avoid profitable trades when the jeopardy (i.e. the combined risks of unfavourable publicity, civil liability, and criminal prosecution) associated with such trades is high, such as avoiding selling shares prior to a negative earnings surprise announcement (see also Ke *et al.*, 2003). Johnson *et al.* (2000) also find that stock price drops are associated with increased securities litigation risk. Downgrading stocks following significant insider sales may trigger large stock price drops, thus raising the risk of shareholder lawsuits and the suspicion of illegal insider trading. Thus, after executing significant stock sales, insiders should have a strong incentive to discourage analysts from issuing recommendation downgrades. In addition, analysts should also have incentives to comply with the insiders' requests in order to maintain good relations with them (Francis and Philbrick, 1993; Ke and Yu, 2006). Therefore, we expect insider selling to have a negative effect on analysts' translational effectiveness.

Second, we consider the influence of trading commissions on translational effectiveness. Because of the short-sale constraint and the fact that there are more potential buyers than sellers, analysts are more likely to issue optimistic recommendations even for firms with poor fundamentals to induce more stock trades. This effect should be stronger for brokerage firms with a large brokerage operation. Consistent with this notion, Irvine (2004) and Jackson (2005) find that analysts generate more trading by issuing optimistic recommendations. Therefore, the incentive to generate more trading commissions can lead analysts to issue a more optimistically biased recommendation than that implied by their expected future firm performance, resulting in lower translational effectiveness. Following Ljungqvist *et al.* (2007), we measure the size of brokerage operation using the number of employed sales representatives (*SALES_REPRESENTATIVES*). Ljungqvist *et al.* (2007) find that analysts' stock recommendation optimism increases with *SALES_REPRESENTATIVES*. However, Ljungqvist *et al.* (2007) did not examine whether trading commissions reduce analysts' translational effectiveness. We expect analysts' translational effectiveness to decrease with *SALES_REPRESENTATIVES*.

Third, we consider the influence of institutional ownership (*INSTITUTION*) on translational effectiveness. Due to their average large ownership stake, institutional investors are believed to be more influential than small investors in financial markets. However, the precise effect of institutional ownership on translational effectiveness is not clear cut because it is unclear how institutional investors use analysts' research. If institutional investors directly base their investment decisions on analysts' explicit recommendations, we expect analysts' recommendation bias to decrease and translational effectiveness to increase with institutional ownership. However, if institutional investors use sell-side analysts' earnings forecasts along with their buy-side research to form independent investment opinions, they should be less concerned about biased recommendations than small investors, who often rely on recommendations in making investment decisions (Malmendier and Shanthikumar, 2007; Mikhail *et al.*, 2007). Furthermore, aggressive institutional investors (e.g. hedge funds) may even use their clout to induce sell-side analysts to deliberately issue more biased recommendations in order to increase their information advantage relative to small investors (see, for example, Chung, 2009; Unger, 2001; Vickers, 2003). As a result, analysts' recommendation bias could increase and translational effectiveness decrease with institutional ownership. Ljungqvist *et al.* (2007) find that analysts' recommendation optimism decreases with institutional ownership, but they did not examine the effect of institutional ownership on analysts' translational effectiveness.[18]

3.3.2 Investor sentiment

A large body of psychological research (see Bagozzi *et al.* (1999) and Forgas (1995) for reviews of the literature) demonstrates that moods can adversely affect judgments and decisions, such as life satisfaction, people, consumer products, and risk assessment. People in good (bad) moods tend to make more positive (more negative) evaluations than people in neutral moods. Prior behavioural finance research has also shown the influence of sunshine, a mood proxy, on stock returns (Hirshleifer and Shumway, 2003; Saunders, 1993).[19] One leading theory for the effects of mood is the mood congruency theory, which states that people in bad moods (good moods) tend to find negative (positive) materials more available or salient (see, for example, Forgas and Bower, 1987; Isen *et al.*, 1978). Clore *et al.* (1994)

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[18] Competition among analysts may potentially increase analysts' translational effectiveness, especially in the presence of independent analysts (Gu and Xue, 2008). Using the number of analysts following as a proxy for analyst competition, we find no evidence that analysts' translational effectiveness is greater for firms with a higher analyst following. We find weak evidence (results untabulated) that dependent analysts' translational effectiveness is greater in the stocks that are also covered by at least one independent analyst (defined as analysts who do not work for investment banks, i.e. both *BOOKRUNNER* and *SYNDICATE* are equal to zero). The two-tailed p value for the interaction between *V/P* and a dummy that indicates the presence of independent analysts is 0.123.

[19] See Hirshleifer (2001) for a review of this literature.

and Forgas (1995) further show that the mood effect is stronger for relatively abstract and complex judgments about which people lack concrete information. There is also evidence that the mood effect is weaker for negative moods than for positive moods (see, for example, Clark and Isen, 1982; Schwarz and Clore, 1983).

Investor sentiment, a mood proxy, will likely affect both earnings forecasts and stock recommendations. However, the evidence from the above psychology literature suggests that the effect of investor sentiment should be stronger for stock recommendations than for earnings forecasts because predicting stock return is more abstract and difficult than forecasting earnings. As a result, analysts who are subject to extremely positive (negative) investor sentiment are more likely to issue optimistic (pessimistic) recommendations regardless of the value of *V/P*.

We use the investor sentiment index (*SENTIMENT*) developed by Baker and Wurgler (2006). *SENTIMENT* is an annual index of six commonly used investor sentiment proxies (i.e. the closed end fund discount, NYSE share turnover, the number of IPOs, the average first-day IPO return, the share of equity issues in total equity and debt issues, and the dividend premium) that is orthogonal to the common business cycle proxies. *SENTIMENT* varies by year but not by firm. To our knowledge, *SENTIMENT* is the most comprehensive measure of investor sentiment in the finance literature. Prior research finds that investor sentiment affects both the time series and cross-section of stock returns (Baker and Wurgler, 2000, 2006; Neal and Wheatley, 1998; Shiller, 1981). We predict the coefficient on *V/P* to decrease with *SENTIMENT*.[20]

An alternative explanation for a negative coefficient on *V/P*×*SENTIMENT* is that *V/P* is less useful as a predictor of future abnormal returns during periods of extreme investor sentiment and thus is relied on less in analysts' recommendations. However, we find no evidence in our sample period that the abnormal return performance of *V/P* is worse during periods of extreme investment sentiment.

3.3.3 Control variables

As noted in Section 3.1, *V/P* omits non-earnings information and may measure a firm's intrinsic value with errors due to either a bad valuation model or bad inputs. Since analysts are not constrained from using non-earnings information, using a better valuation model, or filtering out the noise in bad inputs, their recommendations should be less affected by such measurement problems. Hence, we expect such measurement problems to weaken the positive association between *V/P* and *REC*. More importantly, if *V/P*'s measurement errors are correlated with the variables in *Z*, the predicted coefficients on the interaction terms

[20] With the exception of Chen and Chen (2008), we are not aware of any study that analyses the effect of investor sentiment on analysts' translational effectiveness. Chen and Chen (2008) use the S&P500 index return in the month prior to the consensus recommendation as an investor sentiment proxy but find no evidence that their proxy affects translational effectiveness.

V/P×*Z* would be subject to alternative explanations.

To control for potential measurement errors in *V/P*, we follow Ertimur *et al.* (2007) by including *BM* and *ACCURACY* in *Z*. *BM* is a proxy for the value relevance of a firm's financial statements and analysts' non-earnings information. As growth firms' stock prices are more likely than value firms' stock prices to be comprised of future growth opportunities and intangible assets, growth firms' financial statements may not capture firm value as well as value firms' financial statements. For the same reason, growth firm analysts should have a stronger incentive to search for non-earnings information than value firm analysts. Therefore, we expect the coefficient on *V/P*×*BM* to be positive.[21] *ACCURACY* controls for the quality of analysts' earnings forecasts. Assuming that analysts understand the quality of their own earnings forecasts, analysts' reliance on earnings forecasts in formulating their recommendations should increase with *ACCURACY* (Kim and Verrecchia, 1991). As a result, we predict the coefficient on *V/P*×*ACCURACY* to be positive. Note that conflicts of interest and investor sentiment may also increase analysts' earnings forecast bias and reduce forecast accuracy. However, as explained above, the effects of conflicts of interest and investor sentiment on recommendation bias are expected to be greater. Empirically, none of our regression coefficients of interest are sensitive to the exclusion of *ACCURACY* or *BM* or both.

Prior research shows that experience affects analysts' forecasting performance. Thus, we also use *GENERALEXPERIENCE* and *FIRMEXPERIENCE* to control for the potential effect of experience on analysts' translational effectiveness. Both experience measures are transformed into the natural logarithm in the regressions to reduce skewness. We use both dimensions of analyst experience because it is not clear which dimension matters more. The evidence from the existing literature (see, for example, Clement, 1999; Jacob *et al.*, 1999; Mikhail *et al.*, 1997, 2003) suggests that *GENERALEXPERIENCE* and *FIRMEXPERIENCE* could be proxies for either learning or innate ability or both. To the extent that experience helps increase the translational effectiveness, the coefficient on *V/P* is expected to be larger for more experienced analysts.[22]

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[21] Ertimur *et al.* (2007) also use a loss firm dummy and the adjusted R^2 from the regression of annual stock returns on annual earnings and changes in annual earnings as alternative proxies for the value relevance of financial statements. Untabulated results show that the interaction between *V/P* and the loss dummy is insignificant while the interaction between *V/P* and the adjusted R^2 is significantly positive, consistent with the result using *BM*. We decide not to use the adjusted R^2 as a proxy for the value relevance because using the adjusted R^2 would reduce the sample size for regression model (2) by almost a half.

[22] One may argue that analysts' recommendations reflect analysts' views on both abnormal returns and expected returns. Even if this were the case, omitting the expected return from regression model (2) would not cause inconsistency in the estimated regression coefficients because abnormal returns and expected returns are orthogonal to each other. Nevertheless, we also include the expected return proxy r_e (defined in Section 3.1) and its interaction with the firm/analyst characteristics *Z* in regression model (2). None of the coefficients on *V/P*×*Z* in model (2) are affected.

Table 1 Descriptive Statistics of Regression Variables over the period 1993 to 2005 (N=84,303)[a]

Panel A Descriptive statistics

Variable	Mean	25%	median	75%	S.D.
REC	3.801	3	4	5	0.929
V/P	0.984	0.464	0.765	1.205	1.054
BOOKRUNNER	0.519	0	1	1	0.500
SYNDICATE	0.364	0	0	1	0.481
EQUITYISSUE	0.250	0	0	1	0.433
DEBTISSUE	0.250	0	0	1	0.433
INSIDERSELL	0.250	0	0	1	0.433
SALES_REPRESENTATIVES	1,863.53	0	0	1,021	3,962.49
INSTITUTION	0.610	0.452	0.637	0.792	0.238
SENTIMENT	0.353	0.032	0.160	0.613	0.443
BM	0.602	0.206	0.353	0.579	1.176
ACCURACY	0.108	-0.082	0.084	0.400	0.512
GENERALEXPERIENCE	6.668	2	5	10	5.286
FIRMEXPERIENCE	2.983	1	2	4	3.213

Panel B Pearson (top diagonal) and Spearman (bottom diagonal) correlations (two-tailed p values in parentheses)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	*REC*		0.040 (<0.001)	-0.036 <0.001)	0.035 (<0.001)	0.079 (<0.001)	0.022 (<0.001)	0.006 (0.095)	-0.031 (<0.001)	-0.033 (<0.001)	0.112 (<0.001)	-0.086 (<0.001)	-0.007 (0.048)	-0.018 (<0.001)	-0.073 (<0.001)
(2)	*V/P*	0.046 (<0.001)		-0.014 (<0.001)	0.015 (<0.001)	-0.046 (<0.001)	0.014 (<0.001)	0.023 (<0.001)	-0.017 (<0.001)	0.019 (<0.001)	-0.0126 (<0.001)	-0.052 (<0.001)	-0.005 (0.127)	-0.001 (0.738)	-0.006 (0.075)
(3)	*BOOKRUNNER*	-0.047 (<0.001)	-0.007 (0.040)		-0.786 (<0.001)	0.030 (<0.001)	0.028 (<0.001)	0.027 (<0.001)	0.322 (<0.001)	0.056 (<0.001)	0.052 (<0.001)	0.025 (<0.001)	0.029 (<0.001)	0.062 (<0.001)	0.041 (<0.001)
(4)	*SYNDICATE*	0.044 (<0.001)	0.009 (0.007)	-0.786 (<0.001)		0.032 (<0.001)	-0.021 (<0.001)	-0.025 (<0.001)	-0.267 (<0.001)	-0.057 (<0.001)	-0.038 (<0.001)	-0.040 (<0.001)	-0.018 (<0.001)	-0.044 (<0.001)	-0.024 (<0.001)
(5)	*EQUITYISSUE*	0.081 (<0.001)	-0.078 (<0.001)	0.030 (<0.001)	0.032 (<0.001)		-0.064 (<0.001)	0.135 (<0.001)	-0.036 (<0.001)	-0.080 (<0.001)	0.067 (<0.001)	-0.079 (<0.001)	-0.005 (0.135)	-0.080 (<0.001)	-0.162 (<0.001)
(6)	*DEBTISSUE*	0.022 (<0.001)	-0.003 (0.436)	0.028 (<0.001)	-0.022 (<0.001)	-0.064 (<0.001)		-0.044 (<0.001)	0.030 (<0.001)	-0.026 (<0.001)	0.071 (<0.001)	0.011 (<0.001)	0.003 (0.373)	0.020 (<0.001)	0.005 (0.189)
(7)	*INSIDERSELL*	0.004 (0.312)	0.031 (<0.001)	0.027 (<0.001)	-0.025 (<0.001)	0.135 (<0.001)	-0.044 (<0.001)		0.012 (<0.001)	0.163 (<0.001)	0.046 (<0.001)	-0.128 (<0.001)	0.018 (<0.001)	-0.015 (<0.001)	-0.023 (<0.001)
(8)	*SALES_REPRESENTATIVES*	-0.068 (<0.001)	-0.019 (<0.001)	0.409 (<0.001)	-0.342 (<0.001)	-0.040 (<0.001)	0.044 (<0.001)	0.003 (0.339)		0.032 (<0.001)	0.076 (<0.001)	0.072 (<0.001)	0.027 (<0.001)	0.077 (<0.001)	0.087 (<0.001)
(9)	*INSTITUTION*	-0.033 (<0.001)	0.047 (<0.001)	0.054 (<0.001)	-0.058 (<0.001)	-0.070 (<0.001)	-0.027 (<0.001)	0.154 (<0.001)	0.024 (<0.001)		-0.087 (<0.001)	-0.017 (<0.001)	0.018 (<0.001)	0.037 (<0.001)	0.072 (<0.001)
(10)	*SENTIMENT*	0.099 (<0.001)	-0.116 (<0.001)	0.058 (<0.001)	-0.042 (<0.001)	0.051 (<0.001)	0.080 (<0.001)	0.019 (<0.001)	0.113 (<0.001)	-0.120 (<0.001)		-0.023 (<0.001)	0.008 (0.015)	0.016 (<0.001)	-0.005 (0.195)
(11)	*BM*	-0.169 (<0.001)	-0.030 (<0.001)	0.014 (<0.001)	-0.028 (<0.001)	-0.179 (<0.001)	0.045 (<0.001)	-0.267 (<0.001)	0.015 (<0.001)	-0.048 (<0.001)	-0.048 (<0.001)		-0.013 (<0.001)	-0.044 (<0.001)	-0.009 (0.012)
(12)	*ACCURACY*	-0.029 (<0.001)	-0.011 (0.001)	0.031 (<0.001)	-0.019 (<0.001)	-0.013 (<0.001)	0.009 (0.011)	0.016 (<0.001)	0.048 (<0.001)	0.020 (<0.001)	0.015 (<0.001)	0.010 (0.003)		0.019 (<0.001)	0.031 (<0.001)
(13)	*GENERALEXPERIENCE*	-0.026 (<0.001)	0.018 (<0.001)	0.077 (<0.001)	-0.056 (<0.001)	-0.074 (<0.001)	0.015 (<0.001)	-0.013 (<0.001)	0.088 (<0.001)	0.026 (<0.001)	0.006 (0.092)	0.039 (<0.001)	0.030 (<0.001)		0.549 (<0.001)
(14)	*FIRMEXPERIENCE*	-0.112 (<0.001)	0.013 (<0.001)	0.044 (<0.001)	-0.026 (<0.001)	-0.151 (<0.001)	0.004 (0.266)	-0.018 (<0.001)	0.087 (<0.001)	0.055 (<0.001)	-0.023 (<0.001)	0.111 (<0.001)	0.062 (<0.001)	0.509 (<0.001)	

[a] Variable definitions: *REC* is an analyst's stock recommendation and ranges from 5 (strong buy) to 1 (strong sell); *V/P* is the ratio of a stock's intrinsic value to the stock price two trading days prior to the recommendation announcement date. See Appendix B for other variable definitions.

IV. Results

4.1 Descriptive Statistics

Panel A of Table 1 reports the descriptive statistics for the key regression variables. As expected, analysts' stock recommendations are overly optimistic because the median recommendation is 4 (buy) and there are very few strong sell (1) recommendations. The median *V/P* is only 0.765, while the mean is close to 1. If we interpret *V/P* literally, stocks with *V/P* significantly greater (less) than 1 should be bought (sold), while stocks with *V/P* close to 1 should be held. This decision rule would imply that the median stock recommendation should be a sell, which is inconsistent with analysts' predominantly buy recommendations.

Approximately 88% of the stock recommendations are issued by analysts that belong to brokers with an investment banking business (51.9% for *BOOKRUNNER* and 36.4% for *SYNDICATE*). Before taking the absolute value, the signed investor sentiment is negative for five out of the 13 sample years but small in magnitude relative to the values of the positive investor sentiment. In addition, the variation in investor sentiment is smaller for negative sentiment than for positive sentiment. The most positive investor sentiment is 1.544 in 2000, while the most negative investor sentiment is only -0.173 in 2003. We show in Section 4.3 that the effect of *SENTIMENT* on translational effectiveness is significant for both positive sentiment and negative sentiment. Both general and firm-specific experience varies significantly for the analysts in our sample.

Panel B of Table 1 reports the Pearson (top diagonal) and Spearman (bottom diagonal) correlations for the variables included in Panel A. With a few exceptions, the Pearson correlations among the regression variables are not high. The correlation between *V/P* and *REC* is a small 4% but significant.[23] As expected, the correlation between *GENERALEXPERIENCE* and *FIRMEXPERIENCE* is a significant 0.549 and the correlation between *BOOKRUNNER* and *SYNDICATE* is a significant -0.786. In addition, the correlation between *BOOKRUNNER* and *SALES_REPRESENTATIVES* is a significant 0.322. The other univariate correlations are always below 0.16 in magnitude. Though one may suspect the correlation between *BM* and *V/P* to be high, it is only a significant -0.052.

The Pearson correlations between the two proxies for *V/P*'s measurement error (i.e. *BM* and *ACCURACY*) and other variables in *Z* are always below 0.10 in magnitude, except that the correlation between *BM* and *INSIDERSELL* is -0.128. This evidence suggests that measurement errors in *V/P* may not have a significant impact on the interaction coefficients between *V/P* and other variables in *Z*.

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[23] The significantly positive correlation between *V/P* and REC is different from Bradshaw's (2004) zero or even negative correlation. Consistent with Bradshaw (2004), we find that the Pearson correlation between *V/P* and *REC* is 0.01 and not significant in the period before the 2002/2003 regulatory changes but becomes 0.06 and significantly positive in the period after the changes. Chen and Chen (2008, Table 2) find similar results.

4.2 Results on the Profitability of Recommendations versus *V/P*

Table 2 reports the abnormal returns to stock recommendations (i.e. alpha) from the Fama-French four-factor model for the four types of stock recommendations.[24] Recall that the abnormal return measurement starts from one day prior to the recommendation announcement date and ends either 12 months after the return window starting date or two days before the next recommendation issued by the same analyst, whichever comes first.

Table 2 Regression Results of the Monthly Fama and French Four-Factor Model for Portfolios sorted by Stock Recommendation and V/P[a]

	Consistent buy (N=13,040)	Consistent sell (N=8,991)	Inconsistent buy (N=12,084)	Inconsistent sell (n=8,036)
Alpha	0.0108	-0.0040	-0.0033	0.0060
	(<0.001)	(0.027)	(0.049)	(0.044)
$R_m - R_f$	0.9602	1.1755	1.2205	0.8825
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SMB	-0.0347	0.0670	0.0011	-0.0081
	(0.648)	(0.175)	(0.980)	(0.920)
HML	-0.6333	-0.0377	-0.3013	-0.4202
	(<0.001)	(0.547)	(<0.001)	(<0.001)
MOM	-0.0422	-0.1914	0.0339	-0.2225
	(0.421)	(<0.001)	(0.281)	(<0.001)
Adj R^2	0.773	0.883	0.910	0.704

[a] A recommendation's abnormal return is measured over a period that starts from the trading day prior to the recommendation announcement date and ends 12 months after the return window starting date or two days before the next recommendation issued by the same analyst, whichever comes first. Inconsistent buy is defined as stocks whose analyst recommendation is a strong buy or buy but whose corresponding *V/P* value is in the bottom quartile of the sample. Consistent buy is defined as stocks whose analyst recommendation is a strong buy or buy and whose corresponding *V/P* value is in the top quartile of the sample. Inconsistent sell is defined as stocks whose analyst recommendation is a strong sell, sell, or hold but whose corresponding *V/P* value is in the top quartile of the sample. Consistent sell is defined as stocks whose analyst recommendation is a strong sell, sell, or hold and whose corresponding *V/P* value is in the bottom quartile of the sample. See Table 1 for the definition of *V/P*. Alpha is the intercept from the Fama-French four-factor model. R_m is the monthly return on the CRSP/NYSE/AMEX/NASDAQ value-weighted market index. R_f is the monthly return on the one-month-to-maturity treasury bill. *SMB* is the difference in the value-weighted monthly returns between the small stock portfolio and the large stock portfolio. *HML* is the difference in the value-weighted monthly returns between the high book-to-market stock portfolio and the low book-to-market stock portfolio. See Fama and French (1993) for a detailed discussion on the construction of *SMB* and *HML*. *MOM* is the difference in the equally-weighted monthly returns between the high return momentum stock portfolio (defined as firms with the 30 highest percentage returns over the 11 months ending two months prior to the *MOM* calculation) and the low return momentum stock portfolio (defined as firms with the 30 lowest percentage returns over the 11 months ending two months prior to the *MOM* calculation). The data on $R_m - R_f$, *SMB*, *HML*, and *MOM* are obtained from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html. The Fama-French four-factor model is estimated over the period 1/1/1994 to 12/31/2005 for a total of 144 months. Two-tailed p values are reported in parentheses.

[24] Barber *et al.* (2003) find calendar year 2000 anomalous because analysts' stock recommendations predict future abnormal stock returns in the wrong direction. Our abnormal return results are robust to the exclusion of the year 2000.

The abnormal returns associated with the inconsistent buys and inconsistent sells are opposite to the directions of analysts' recommendations. The monthly alpha is -0.33% for inconsistent buys and +0.60% for inconsistent sells. Both alphas are significant and economically significant, suggesting that investors who subscribe to analysts' research reports are better off if they follow the *V/P* signal, which is a summary measure of analysts' earnings forecasts, rather than analysts' recommendations. The abnormal returns for the inconsistent sells are surprising given that analysts are often accused of issuing too many optimistic recommendations. In addition, the number of inconsistent sells is not trivial relative to the number of inconsistent buys (8,036 versus 12,084). Overall, these results suggest that analysts' recommendations do not fully incorporate the information in their earnings forecasts, a finding consistent with Bradshaw (2004), even though he computes his one-year abnormal return beginning on the 15th day of the month subsequent to the date of the consensus recommendation.[25] In addition, these results suggest the measurement error in *V/P* is not large enough to render *V/P* less useful than recommendations as a predictor of future abnormal returns.

The abnormal returns associated with the consistent buys and consistent sells are consistent with analysts' recommendations. The monthly alpha is +1.08% for consistent buys and -0.40% for consistent sells. However, as cautioned in Section 3.2, the significant abnormal returns on consistent buys and consistent sells do not necessarily imply that analysts' recommendations have fully incorporated the information in their earnings forecasts.

4.3 Results on the Determinants of Analysts' Translational Effectiveness

4.3.1 Primary results

After establishing analysts' failure to fully translate their earnings forecasts into recommendations, we examine the determinants of analysts' translational effectiveness. Column (1) of Table 3 reports the regression results of model (2) using the entire sample period (1993–2005). The regression result in column (2) is discussed in Section 4.3.2, and the standardised coefficients in column (3) are discussed in Section 4.3.3. To ease the interpretation of regression coefficients, we run regression model (2) using the OLS method, although the inferences are qualitatively the same using the ordered Probit method. We use Cook's (1977) distance statistic to reduce the influence of outliers and report robust p values using STATA's cluster command by stock ID (see Rogers, 1993). Results are similar if p values are computed using the Fama and MacBeth (1973) approach, except that we cannot estimate the effect of *SENTIMENT* because its values vary by year but not by firm. There is no evidence of multicollinearity in our regression model (2).

[25] The abnormal returns for the inconsistent buys and inconsistent sells are qualitatively the same if the return window starts from the 8th trading day following the recommendation announcement date (untabulated), suggesting that most of the abnormal returns are realised in the period subsequent to the recommendation announcement date.

Table 3 OLS Regression Results on the Determinants of Analysts' Translational Effectiveness[a]

		(1)	(2)	(3)
Dependent variable = *REC*	Prediction on interaction	Model with *BM* and *ACCURACY*	Model without *BM* and *ACCURACY*	Standardised coefficient[b]
V/P		0.143	0.160	
		(0.013)***	(0.013)***	
Ln(*GENERALEXPERIENCE*)		0.033	0.039	
		(0.005)***	(0.006)***	
V/P×Ln(*GENERALEXPERIENCE*)	+	0.003	0.002	0.003
		(0.004)	(0.004)	
Ln(*FIRMEXPERIENCE*)		-0.126	-0.131	
		(0.007)***	(0.007)***	
V/P×Ln(*FIRMEXPERIENCE*)	+	0.015	0.019	0.012
		(0.005)***	(0.005)***	
BOOKRUNNER		-0.036	-0.029	
		(0.013)***	(0.013)***	
V/P×BOOKRUNNER	-	-0.029	-0.033	-0.015
		(0.009)***	(0.009)***	
SYNDICATE		-0.005	0.000	
		(0.013)	(0.013)	
V/P×SYNDICATE	-	-0.020	-0.021	-0.010
		(0.009)**	(0.009)**	
EQUITYISSUE		0.126	0.138	
		(0.011)***	(0.012)***	
V/P×EQUITYISSUE	-	-0.031	-0.033	-0.013
		(0.007)***	(0.007)***	
DEBTISSUE		0.012	0.010	
		(0.011)	(0.011)	
V/P×DEBTISSUE	?	-0.001	-0.000	-0.000
		(0.007)	(0.007)	
INSIDERSELL		0.027	0.043	
		(0.012)***	(0.012)***	
V/P×INSIDERSELL	-	-0.037	-0.037	-0.016
		(0.008)***	(0.008)***	
ln(*SALES_REPRESENTATIVES*)		-0.016	-0.018	
		(0.001)***	(0.001)***	
V/P×ln(*SALES_REPRESENTATIVES*)	-	-0.006	-0.005	-0.023
		(0.001)***	(0.001)***	
INSTITUTION		0.161	0.173	
		(0.022)***	(0.023)***	
V/P×INSTITUTION	?	-0.067	-0.073	-0.016
		(0.015)***	(0.015)***	
SENTIMENT		0.364	0.442	
		(0.020)***	(0.019)***	
V/P×SENTIMENT	-	-0.047	-0.043	-0.021
		(0.010)***	(0.010)***	
BM		-0.084		
		(0.004)***		
V/P×BM	+	0.016		0.019
		(0.003)***		
ACCURACY		-0.034		
		(0.008)***		
V/P×ACCURACY	+	0.014		0.007
		(0.006)**		
Year fixed effects		YES	YES	
Observations		80,611	80,883	
R-squared		0.081	0.072	

[a] "×" denotes the interaction of two variables. See Table 1 and Appendix B for variable definitions. Outliers are deleted using Cook's (1977) distance statistic. The standard errors in parentheses are adjusted for heteroskedasticity and serial autocorrelation by stock ID using STATA's cluster command (Rogers, 1993). *, **, and *** indicate a two-tailed significance level of 10%, 5%, and 1%, respectively.

[b] The standardised coefficient on an interaction variable (say *V/P×Z*) is computed as the coefficient on the interaction variable in column (1) multiplied by one standard deviation of *Z*.

As predicted, the coefficient on *V/P* is significantly positive, suggesting that firms with higher *V/P*s are associated with more favourable recommendations. Consistent with prior research, investment banking pressure reduces analysts' translational effectiveness. Specifically, the coefficients on *V/P*×*BOOKRUNNER*, *V/P*×*SYNDICATE*, and *V/P*×*EQUITYISSUE* are all significantly negative. As expected, the coefficient on *V/P*×*DEBTISSUE* is insignificant, suggesting that debt financing does not affect analysts' translational effectiveness.

More importantly, we find that insider trading, trading commissions, institutional ownership, and investor sentiment all reduce analysts' translational effectiveness. Specifically, the coefficients on *V/P*×*INSIDERSELL*, *V/P*×ln(*SALES_REPRESENTATIVES*), *V/P*×*INSTITUTION*, and *V/P*×*SENTIMENT* are all significantly negative. The negative effect of institutional ownership on translational effectiveness is interesting in light of Ljungqvist *et al.*'s (2007) finding that the presence of institutional ownership helps reduce recommendation optimism. The difference in results suggests that the influence of institutional ownership on analysts is subtle and deserves more research in the future. The investor sentiment result is also noteworthy because analysts are supposed to be sophisticated intermediaries who are less influenced by market sentiment. Untabulated regression results further show that the negative coefficient on *V/P*×*SENTIMENT* holds for both positive sentiment and negative sentiment, although the magnitude of the coefficient is much larger for positive investor sentiment. This latter finding is consistent with the theory that the effect of positive mood is more pronounced (see, for example, Clark and Isen, 1982; Schwarz and Clore, 1983).

Regarding the control variables, the coefficient on *V/P*×ln(*GENERALEXPERIENCE*) is insignificant but the coefficient on *V/P*×ln(*FIRMEXPERIENCE*) is significantly positive, suggesting that firm-specific forecasting experience, but not general forecasting experience, helps increase analysts' translational effectiveness. There is evidence that the relation between *V/P* and *REC* is moderated by measurement errors in *V/P*. The coefficients on *V/P*×*BM* and *V/P*×*ACCURACY* are both significantly positive. These two results suggest that analysts' recommendations rely on *V/P* more heavily when financial statements better capture firm value or non-earnings information is less important (i.e. higher *BM*) or when earnings forecasts are more accurate (i.e. higher *ACCURACY*).

We conduct two more robustness tests to rule out alternative explanations for the regression results in column (1) of Table 3. First, we control for firm size and its interaction with *V/P* in regression model (2) to eliminate potential confounding factors associated with firm size. The results on our variables of interest are unaffected except that the coefficient on *V/P*×*INSIDERSELL* becomes insignificant (results untabulated). The reduced significance on the coefficient on *V/P*×*INSIDERSELL* is expected because insider selling increases with firm size (see Ke *et al.*, 2003).

Second, we allow the coefficient on *BM* to vary with the firm/analyst characteristics contained in *Z* in regression model (2). As our intrinsic value estimate *V* is the sum of a firm's book value of equity and the present value of future abnormal earnings (see equation (1)), this sensitivity check intends to rule out the alternative explanation that the significant coefficients on the interactions between *V/P* and the firm/analyst characteristics *Z* in model (2) are due to the book value of equity rather than the earnings forecasts. Except for the insignificant interaction coefficient on *V/P×BM*, the other interaction coefficients between *V/P* and *Z* remain consistent with expectations and significant (results untabulated). This evidence suggests that the documented interaction effects between *V/P* and *Z* are not driven by the book-to-market interaction effect.

4.3.2 Measurement error in *V/P*

As noted in Section 3.1, *V/P* could measure a firm's intrinsic value with errors. To assess the significance of *V/P*'s measurement error and its impact on our results in Tables 2 and 3, we perform two separate analyses. Our first analysis involves rerunning regression model (2) after excluding *BM* and *ACCURACY* and their interactions with *V/P*. As *BM* and *ACCURACY* are expected to be correlated with the measurement error in *V/P*, the coefficients on *V/P×Z* from this revised regression should change significantly to the extent that the measurement error is material and significantly correlated with the other variables in *Z*. As shown in column (2) of Table 3, we find little evidence that omitting the variables associated with *BM* and *ACCURACY* has a significant impact on the coefficients on the other interaction variables with *V/P*. This result suggests that while measurement error in *V/P* does reduce the association between *V/P* and *REC*, it does not significantly affect our inferences on the interested determinants of analysts' translational effectiveness.

Our second analysis involves replicating Table 2 using the predicted recommendations derived from regression model (2) in column (1) of Table 3. We use the predicted values of REC to assign our sample observations into one of the five recommendation categories in the same proportion as the actual recommendations.[26] For example, 1.83% of the recommendations in our sample are strong sells and thus we assign the bottom 1.83% of the predicted recommendations to the strong sell category.

This sensitivity check serves two important purposes. First, it allows us to directly demonstrate whether the documented abnormal returns for the inconsistent buys and inconsistent sells in Table 2 are attributed to the identified determinants *Z* in Table 3. Second, it allows us to rule out measurement error in *V/P* as an alternative explanation for the predicted coefficients on the interactions between *V/P* and the conflicts of interest and investor sentiment variables. Specifically, to the extent that the predicted coefficients on *V/P×Z* in regression model (2) are due to measurement error in *V/P* (i.e. analysts'

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[26] Results are similar if we assign the top tercile of the predicted recommendations to buys and the bottom tercile to sells.

recommendations rationally attach a lower weight to *V/P* that has a greater measurement error), the predicted recommendations should be more informative than *V/P* in predicting future abnormal returns. However, if the predicted coefficients on $V/P \times Z$ in regression model (2) are due to analysts' conflicts of interest and investor sentiment, the predicted recommendations should be less informative than *V/P* in predicting future abnormal returns.

Panel A of Table 4 shows the result of this analysis. The Fama-French four-factor alpha based on the predicted recommendations is 0.0098 ($p<0.001$) for consistent buys, -0.0023 ($p=0.218$) for consistent sells, -0.0045 ($p=0.039$) for inconsistent buys, and 0.0095 ($p=0.003$) for inconsistent sells, which are nearly identical to those in Table 2. This evidence suggests that the predicted coefficients on $V/P \times Z$ in regression model (2) are more likely due to analysts' conflicts of interest and investor sentiment rather than measurement error in *V/P*.

Table 4 Regression Results of the Monthly Fama and French Four-Factor Model for Portfolios sorted by Predicted Recommendation and *V/P*[a]

Panel A Predicted recommendations of model (2) (full model) versus *V/P*

	Consistent buy (N=14,069)	Consistent sell (N=8,969)	Inconsistent buy (N=12,106)	Inconsistent sell (N=7,007)
Alpha	0.0098	-0.0023	-0.0045	0.0095
	(<0.001)	(0.218)	(0.039)	(0.003)
$R_m - R_f$	0.9174	1.1998	1.2491	0.8570
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SMB	-0.0437	-0.0384	0.0805	-0.0683
	(0.578)	(0.441)	(0.177)	(0.426)
HML	-0.6375	0.1870	-0.2633	-0.6415
	(<0.001)	(0.004)	(<0.001)	(<0.001)
MOM	-0.0951	-0.0854	-0.0386	-0.1754
	(0.081)	(0.014)	(0.347)	(<0.001)
Adj R^2	0.752	0.857	0.864	0.707

Panel B Predicted recommendations of model (2) (excluding the investment banking pressure variables) versus *V/P*

	Consistent buy (N=15,043)	Consistent sell (N=9,937)	Inconsistent buy (N=11,138)	Inconsistent sell (N=6,033)
Alpha	0.0098	-0.0019	-0.0084	0.0049
	(<0.001)	(0.351)	(0.012)	(0.212)
$R_m - R_f$	0.9134	1.1915	1.2236	0.8283
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SMB	-0.0449	-0.0671	0.0343	-0.1449
	(0.566)	(0.238)	(0.705)	(0.174)
HML	-0.6480	0.1033	-0.2693	-0.1949
	(<0.001)	(0.153)	(0.020)	(0.150)
MOM	-0.0953	-0.1399	-0.0068	-0.4357
	(0.078)	(<0.001)	(0.914)	(<0.001)
Adj R^2	0.756	0.833	0.719	0.558

Panel C Predicted recommendations of model (2) (excluding insider trading, trading commissions, institutional ownership, and investor sentiment) versus *V/P*

	Consistent buy (N=16,557)	Consistent sell (N=11,549)	Inconsistent buy (N=9,526)	Inconsistent sell (N=4,519)
Alpha	0.0098	-0.0040	-0.0042	0.0002
	(<0.001)	(0.042)	(0.093)	(0.967)
$R_m - R_f$	0.9108	1.1279	1.2352	1.1347
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SMB	-0.0387	0.0634	0.0333	0.0382
	(0.631)	(0.231)	(0.630)	(0.761)
HML	-0.7291	-0.0457	-0.4687	0.1153
	(<0.001)	(0.496)	(<0.001)	(0.470)
MOM	-0.1612	-0.1102	-0.0954	-0.3623
	(0.004)	(0.003)	(0.047)	(<0.001)
Adj R^2	0.763	0.853	0.844	0.542

[a] A recommendation's abnormal return is measured over a period that starts from the trading day prior to the recommendation announcement date and ends either 12 months after the return window starting date or two days before the next recommendation issued by the same analyst, whichever comes first. Predicted recommendations in all three panels are calculated on the basis of the estimated regression coefficients reported in column (1) of Table 3. The predicted recommendations in Panel A use all the estimated coefficients from model (2). The predicted recommendations in Panel B use the estimated coefficients other than those associated with the investment banking variables (i.e. *BOOKRUNNER*, *SYNDICATE*, *EQUITYISSUE*, and *DEBTISSUE*). The predicted recommendations in Panel C use the estimated coefficients other than those associated with ln(*SALES_REPRESENTATIVES*), *INSIDERSELL*, *INSTITUTION*, and *SENTIMENT*. We use the predicted values of *REC* to assign observations into one of the five recommendation categories in the same proportion as the actual recommendations. Then, we define inconsistent buys/sells and consistent buys/sells in the same way as in Table 2. See Table 1 for the definitions of other variables. Alpha is the intercept from the Fama-French four-factor model. R_m is the monthly return the CRSP/NYSE/AMEX/NASDAQ value-weighted market index. R_f is the monthly return on the one-month-to-maturity treasury bill. *SMB* is the difference in the value-weighted monthly returns between the small stock portfolio and the large stock portfolio. *HML* is the difference in the value-weighted monthly returns between the high book-to-market stock portfolio and the low book-to-market stock portfolio. See Fama and French (1993) for a detailed discussion on the construction of *SMB* and *HML*. *MOM* is the difference in the equally-weighted monthly returns between the high return momentum stock portfolio (defined as firms with the 30 highest percentage returns over the 11 months ending two months prior to the *MOM* calculation) and the low return momentum stock portfolio (defined as firms with the 30 lowest percentage returns over the 11 months ending two months prior to the *MOM* calculation). The data on $R_m - R_f$, *SMB*, *HML*, and *MOM* are obtained from Kenneth French's web site at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html. The Fama-French four-factor model is estimated over the period 1/1/1994 to 12/31/2005 for a total of 144 months. Two-tailed p values are reported in parentheses.

4.3.3 Economic significance of insider trading, trading commissions, institutional ownership, and investor sentiment

As investment banking pressure was a major focus of prior research on analysts' conflicts of interest, it is informative to compare the economic significance of our newly identified determinants of translational effectiveness and that of investment banking pressure. We provide two pieces of evidence. First, we use the regression coefficients in column (1) of Table 3 to show that compared with the investment banking pressure, the effect of insider trading, trading commissions, institutional ownership, and investor sentiment on analysts' translational effectiveness is economically significant. The last column of Table 3 uses the coefficient estimates in column (1) of Table 3 to calculate the expected change in the coefficient on *V/P* for a one standard deviation increase in a factor, referred to as a standardised coefficient. For the three significant investment banking factors considered in prior studies (i.e. *BOOKRUNNER*, *SYNDICATE*, and *EQUITYISSUE*), the largest standardised coefficient in magnitude is 0.015 for *BOOKRUNNER*. By comparison, the standardised coefficients on all the other significant determinants ignored in prior studies (i.e. *INSIDERSELL*, ln(*SALES_REPRESENTATIVES*), *INSTITUTION*, and *SENTIMENT*) are always larger than 0.015 in magnitude. In addition, the sum of the standardised coefficients for the four new determinants is twice as much as the sum of the three standardised coefficients for investment banking pressure.

Second, we compare the differential contributions of the four new factors versus the investment banking pressure proxies to the abnormal returns on the inconsistent buys and inconsistent sells. Specifically, we rerun the abnormal return analysis in Panel A of Table 4 after using the estimated coefficients in column (1) of Table 3 to calculate two versions of predicted recommendations: a) the predicted recommendations consider only the effects of the four new factors and exclude all the regression variables associated with the investment banking pressure (i.e. *BOOKRUNNER*, *SYNDICATE*, *EQUITYISSUE*, and *DEBTISSUE*); b) the predicted recommendations consider only the effect of the investment banking pressure and exclude all the regression variables associated with the four new factors (i.e. ln(*SALES_REPRESENTATIVES*), *INSIDERSELL*, *INSTITUTION*, and *SENTIMENT*). Panel B of Table 4 reports the abnormal returns on the four types of predicted recommendations that consider only the four new factors, while Panel C of Table 4 reports the abnormal returns on the four types of predicted recommendations that consider only the investment banking pressure. As our primary interest is analysts' translational effectiveness, we focus on the abnormal returns on the inconsistent recommendations only.

There are two key findings from Panels B and C. First, both investment banking pressure and the four new factors reduce analysts' translational effectiveness and thus the recommendation informativeness. As shown in Panel B, when we only consider the four new factors in computing the predicted recommendations, the abnormal return on inconsistent buys is still significantly negative and the abnormal return on inconsistent sells is positive though insignificant (two-tailed p=0.212). As shown in Panel C, when we only consider the investment banking pressure in computing the predicted recommendations, the abnormal return on inconsistent buys is marginally significantly negative (two-tailed p=0.093). However, the abnormal return on inconsistent sells is small and insignificant (two-tailed p=0.967), suggesting that the significant abnormal return on inconsistent sells in Panel A of Table 4 is not driven by the investment banking pressure. Second, the combined influence of the four new factors on translational effectiveness is as important as (if not greater than) the effect of investment banking pressure. The magnitudes of the abnormal returns on inconsistent buys and inconsistent sells are larger in Panel B than in Panel C.

4.3.4 Results on the determinants of analysts' translational effectiveness before and after the 2002/2003 regulatory changes

The analyst profession underwent significant changes during the latter part of our sample period. In response to numerous accounting scandals and the alleged roles of analysts in issuing biased stock recommendations to help their brokers win investment banking business, several regulatory bodies changed the rules governing sell-side analysts' conduct. On 10 May 2002, the NYSE and NASD modified conduct rules governing sell-side analysts by amending Rule 472 and Rule 2711, respectively. In December 2002, the New York attorney general, the SEC, and the seven largest investment banks reached a research analyst global settlement that separates analyst research from investment banking. Finally, on 14 April 2003, the SEC implemented regulation AC (analyst certification), which requires certifications by individual analysts about their independence and due diligence in research reports. In addition to the above changes that directly targeted analysts, there were also many significant events around 2002, such as the passing of the Sarbanes and Oxley Act and the prosecution of many high-profile white collar criminals.

Barniv *et al.* (2009), Chen and Chen (2009), and Ertimur *et al.* (2007) show that the effect of investment banking pressure on analysts' translational effectiveness is reduced in the period subsequent to the 2002/2003 regulatory changes discussed above. To determine whether the influence of insider trading, trading commissions, institutional ownership, and investor sentiment on analysts' translational effectiveness changes significantly around the same regulatory events, Table 5 reports the results of regression model (2) for the two periods before and after 10 May 2002 separately, the same cut-off used in Ertimur *et al.* (2007). The results are robust to using 14 April 2003 as the cut-off.

Consistent with prior research, the significantly negative coefficients on *V/P*×*BOOKRUNNER*, *V/P*×*SYNDICATE*, and *V/P*×*EQUITYISSUE* are limited to the pre-regulatory-change period only. The coefficients on *V/P*×*BOOKRUNNER*, *V/P*×*SYNDICATE*, and *V/P*×*EQUITYISSUE* are all significantly different between the two time periods. With the exception of trading commissions, the effects of insider trading, institutional ownership, and investor sentiment on analysts' translational effectiveness are all significant in both time periods. The coefficient on *V/P*×ln(*SALES_REPRESENTATIVES*) is significant in the pre-regulatory-change period and insignificant for the post-regulatory-change period, but the coefficient on *V/P*×ln(*SALES_REPRESENTATIVES*) is not significantly different between the two time periods. Interestingly, the coefficients on *V/P*×*INSIDERSELL* and *V/P*×*SENTIMENT* are significantly more negative in the post-regulatory-change period than in the pre-regulatory-change period. These results suggest that the 2002/2003 regulatory changes have not completely eliminated all the forces that reduce analysts' translational effectiveness. Our results shed light on why analysts' recommendations post the 2002/2003 regulatory changes continue to be biased (see Barniv *et al.*, 2009).

Table 5 OLS Regression Results on the Determinants of Analysts' Translational Effectiveness for the Two Periods Before and After the 2002/2003 Regulatory Changes[a]

Dependent Variable = *REC*	Pre-regulatory-change period	Post-regulatory-change period
V/P	0.169	0.150
	(0.017)***	(0.025)***
ln(*GENERALEXPERIENCE*)	0.022	0.049
	(0.007)***	(0.010)***
V/P×ln(*GENERALEXPERIENCE*)	0.012	-0.005
	(0.005)**	(0.006)
ln(*FIRMEXPERIENCE*)	-0.120	-0.133
	(0.008)***	(0.013)***
V/P×ln(*FIRMEXPERIENCE*)	-0.012	0.052
	(0.006)*	(0.008)***
BOOKRUNNER	-0.050	-0.026
	(0.017)***	(0.022)
V/P×BOOKRUNNER	-0.052	-0.004
	(0.013)***	(0.015)
SYNDICATE	-0.051	0.063
	(0.017)***	(0.023)***
V/P×SYNDICATE	-0.040	-0.004
	(0.013)***	(0.015)
EQUITYISSUE	0.168	0.015
	(0.013)***	(0.022)
V/P×EQUITYISSUE	-0.050	0.022
	(0.009)***	(0.013)*
DEBTISSUE	0.006	0.059
	(0.013)	(0.023)**
V/P×DEBTISSUE	0.005	-0.025
	(0.009)	(0.013)**
INSIDERSELL	0.001	0.076
	(0.015)	(0.021)***
V/P×INSIDERSELL	-0.023	-0.063
	(0.011)**	(0.013)***
ln(*SALES_REPRESENTATIVES*)	-0.007	-0.041
	(0.001)***	(0.002)***
V/P×ln(*SALES_REPRESENTATIVES*)	-0.004	-0.001
	(0.001)***	(0.001)
INSTITUTION	0.274	-0.047
	(0.026)***	(0.042)
V/P×INSTITUTION	-0.088	-0.051
	(0.018)***	(0.026)**
SENTIMENT	0.248	0.000
	(0.021)***	(0.000)
V/P×SENTIMENT	-0.025	-0.395
	(0.011)**	(0.075)***

BM	-0.093	-0.066
	(0.006)***	(0.006)***
V/P×BM	-0.002	0.018
	(0.004)	(0.004)***
ACCURACY	-0.054	0.014
	(0.010)***	(0.016)
V/P×ACCURACY	0.000	0.024
	(0.008)	(0.010)**
Year fixed effects	YES	YES
Observations	51966	28663
R-squared	0.057	0.061
	Two-tailed p value for the null hypothesis: the coefficient in the pre-regulatory-change period = the coefficient in the post-regulatory-change period	
V/P×BOOKRUNNER	0.015	
V/P×SYNDICATE	0.070	
V/P×EQUITYISSUE	<0.001	
V/P×DEBTISSUE	0.051	
*V/*P×ln(*SALES_REPRESENTATIVES*)	0.121	
V/P×INSIDERSELL	0.017	
V/P×INSTITUTION	0.233	
V/P×SENTIMENT	<0.001	

[a] The pre-regulatory-change period includes stock recommendations issued before 10 May 2002, and the post-regulatory-change period includes stock recommendations issued after 9 May 2002. "×" denotes the interaction of two variables. See Table 1 and Appendix B for other variable definitions. Outliers are deleted using Cook's (1977) distance statistic. The standard errors in parentheses are adjusted for heteroskedasticity and serial autocorrelation by stock ID using STATA's cluster command (Rogers, 1993). *, **, and *** indicate a two-tailed significance level of 10%, 5%, and 1%, respectively.

V. Conclusion

While a large body of research has studied analysts' earnings forecasts or stock recommendations in isolation, there is little research on the factors that determine the effectiveness with which analysts translate their earnings forecasts into recommendations (referred to as translational effectiveness). Prior research (see Barniv *et al.*, 2009; Chen and Chen, 2009; Ertimur *et al.*, 2007) shows that the influence of investment banking pressure on analysts' translational effectiveness is reduced in the period subsequent to the 2002/2003 regulatory changes. This study identifies four new factors that reduce analysts' translational effectiveness: insider trading, trading commissions, institutional ownership, and investor sentiment. For the sample period 1993 to 2005, we find that the combined influence of our new factors on translational effectiveness is as large as (if not greater than) the influence of investment banking pressure. While we confirm prior research that the 2002/2003 regulatory changes have reduced the influence of investment banking pressure on translational effectiveness, the effect of insider trading, institutional ownership, and investor sentiment on translational effectiveness remains significant or becomes stronger.

Analysts are a major user of financial data prepared by accountants and serve as information gatekeepers for many investors. Thus, it is crucial to understand how well analysts process complex financial information to produce earnings forecasts and how well they translate earnings forecasts into stock recommendations. The contribution of this study is to identify a comprehensive list of factors that influence analysts' translational effectiveness. Our results should be of particular interest to unsophisticated investors who routinely base their investment decisions on analysts' recommendations. Our results suggest that even in the post-regulatory-change period, investors should exercise continued caution when interpreting the recommendations issued by analysts who follow firms with high insider selling and high institutional ownership during periods of extreme investor sentiment.

The effect of investor sentiment on analysts' translational effectiveness is surprising because analysts are often assumed to be sophisticated information processors and thus should be less likely subject to market sentiment. Given the lack of research in this area, more research is warranted to better understand the potential influence of psychological biases on analysts' information processing. For example, future researchers may develop more refined psychological proxies (e.g. at the individual analyst level) so that more refined research hypotheses can be tested.

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Appendix A: Definitions of the terms included in valuation model (1)

s = stock recommendation date

FY1 = one-year-ahead EPS forecast (for fiscal year t) issued at time *s*

FY2 = two-year-ahead EPS forecast (for fiscal year t+1) issued at time *s*

LTG = long-term earnings growth forecast issued at time *s*; missing *LTG* is replaced by the growth rate implied from the one-year-ahead and two-year-ahead earnings forecasts.

k = dividend payout ratio in year *t*-1, defined as the common stock dividends paid in the most recent year (Compustat #21) divided by net income before extraordinary items (Compustat # 237). Following Frankel and Lee (1998), if Compustat #237≤0, *k* is defined as Compustat #21 divided by 6% of total assets, which is the average long-run return on assets estimated in Frankel and Lee (1998).[27]

B_{t-1} = book value of common shareholders' equity at year *t*-1 (Compustat #60)

$B_t = B_{t-1}[1 + FROE_t(1-k)]$

$B_{t+1} = B_t[1 + FROE_{t+1}(1-k)]$

$B_{t+2} = B_{t+1}[1 + FROE_{t+2}(1-k)]$

$FROE_t$ = forecasted return on equity for year t and is defined as $FY1/[(B_{t-1} + B_{t-2})/2]$

$FROE_{t+1} = FY2/[(B_t + B_{t-1})/2]$

$FROE_{t+2} = [FY2(1+LTG)]/[(B_{t+1} + B_t)/2]$ if *LTG* is available

$FROE_{t+2} = FROE_{t+1}$ if *LTG* is missing

r_e = annualised cost of equity, defined as the sum of the industry risk premium calculated using Fama and French's (1997) three-factor model (Table 7, last column) and a risk-free rate equal to the average annualised 30-day t-bill rate before the recommendation date.

[27] The mean (median) return on assets during our sample period is 7% (6%), not significantly different from the 6% reported in Frankel and Lee (1998).

Appendix B: Definitions of variables included in regression model (2)

BOOKRUNNER = a time invariant dummy variable that equals 1 if a brokerage house served as an equity offering book runner in at least 11 of the 23 years over the period 1980 to 2002, and zero otherwise. The raw data used to define *BOOKRUNNER* and *SYNDICATE* was provided by Ke and Yu (2006), who hand collected the data for the period 1980 to 2002 only.[28]

SYNDICATE = a time invariant dummy variable that equals 1 if a brokerage firm served as an equity offering book runner for fewer than 11 years or only as a syndicate over the period 1980 to 2002, and zero otherwise.

EQUITYISSUE = a dummy that equals 1 if the net cash received from the sale (and/or purchase) of common and preferred stock less cash dividends paid (COMPUSTAT annual data item 108 less COMPUSTAT annual data item 115 less COMPUSTAT annual data item 127) scaled by the average total assets during the fiscal year prior to the recommendation year is in the top quartile of the sample, and zero otherwise.

DEBTISSUE = a dummy that equals 1 if the net cash received from the issuance (and/or reduction) of debt (COMPUSTAT annual data item 111 less COMPUSTAT annual data item 114 plus COMPUSTAT annual data item 301) scaled by the average total assets during the fiscal year prior to the recommendation year is in the top quartile of the sample, and zero otherwise.

INSIDERSELL = 1 if the average insider selling (in 1992 dollars) by all corporate officers and directors during the calendar year prior to the recommendation year is in the top quartile of the sample, and zero otherwise.

Ln(*SALES_REPRESENTATIVES*) = the natural logarithm of the number of sales representatives employed by a brokerage firm in the year of a recommendation.[29]

INSTITUTION = total institutional ownership as a fraction of total common shares outstanding measured at the beginning of the calendar quarter in which a recommendation is issued.

SENTIMENT = the absolute value of investor sentiment in the year of the stock recommendation; this variable is used in Baker and Wurgler (2006) and is available at http://pages.stern.nyu.edu/~jwurgler (see Section 3.3.2 for details).

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[28] We believe that *BOOKRUNNER* and *SYNDICATE* defined using the 1980-2002 data should be valid for the last three years of our sample period 1993 to 2005 because a brokerage firm's business type does not change often. Ke and Yu (2006) show that their results are robust to using alternative cutoffs of 15 years and 23 years to define *BOOKRUNNER* and *SYNDICATE*.

[29] We thank Alexander Ljungqvist for providing us with this data over the period 1994 to 2002. We hand collected the data for the remaining years following the same procedures described in Ljungqvist *et al.* (2007).

BM = the ratio of book value to market value of common equity at the fiscal year end prior to the stock recommendation date.

ACCURACY = one-year-ahead earnings forecast accuracy. Following Ertimur *et al.* (2007), *ACCURACY* is defined as $-1 \times \frac{AFE_{ijs} - \overline{AFE_{is}}}{\overline{AFE_{is}}}$, where AFE_{ijs} is the absolute forecast error (i.e. one-year-ahead earnings forecast *FY1* minus the realised earnings) of analyst *j* for stock *i* on the recommendation date *s*, and $\overline{AFE_{is}}$ is the mean absolute forecast error of the latest earnings forecasts issued by all analysts that follow firm *i* over the 90 days up to the stock recommendation date *s*. Higher values of *ACCURACY* represent more accurate earnings forecasts.

GENERALEXPERIENCE = the number of years an analyst issued earnings forecasts for any firm prior to the recommendation year.

FIRMEXPERIENCE = the number of years an analyst issued earnings forecasts for firm *i* prior to the recommendation year.